EVALUATION OF EMPIRICALLY DERIVED PVT PROPERTIES FOR NIGERIAN CRUDE OILS

BY

ADEEYO YISA ADEMOLA

A Thesis Presented to the

DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

PETROLEUM ENGINEERING

FEBRUARY 2005

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by ADEEYO YISA ADEMOLA under the direction of his thesis advisor and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of MASTER OF SCIENCE IN PETROLEUM ENGINEERING.

Thesis Committee

M. A. Marhoun

Dr. Muhammad Ali Al-Marhoun
(Advisor)

H. Y. Al-Yousef

Dr. Hasan Yousef Al-Yousef
(Member)

S. Osman

Dr. El-Sayed Ahmed Osman
(Member)

Dr. Sidqi Ahmad Abu-Khamsin
(Department Chairman)

Dr. Mohammad Al-Ohali
(Dean of Graduate Studies)

عمادة الدراسات العليا
DEANSHIP OF GRADUATE STUDIES

Date: 20 February 2005

THESIS ABSTRACT

Name: **ADEEYO YISA ADEMOLA**

Title: **EVALUATION OF EMPIRICALLY DERIVED PVT PROPERTIES FOR NIGERIAN CRUDE OILS**

Major Field: **PETROLEUM ENGINEERING**

Date of Degree: **JANUARY 2005**

This study presents an evaluation and tuning/recalculation of coefficients (using regression analysis) of some PVT correlations to estimating bubblepoint pressure (Pb), Solution gas-oil ratio (GOR), oil formation volume factor at bubblepoint (FVF), gas-saturated oil and dead-oil viscosity against a set of PVT data collected from different locations in Nigeria.

Neural network models are also developed for all five PVT parameters.

Statistical and graphical tools have been used to compare the performance of the correlations. Best correlation has been identified for each PVT parameter. Correlations performance was also compared with neural network models.

The results of this study show that higher accuracy was obtained when correlations are tuned to the regional data; that present practice in Nigeria of using only Standing and Vasquez & Beggs correlations for Pb, Rs and Bob estimation is not the optimum. Also, Neural Network models' predictions are better for all PVT properties studied

MASTER OF SCIENCE

KING FAHD UNIVERSITY OF PETROLEUM AND MINERALS

DHAHRAN SAUDI ARABIA

JANUARY 2005

ملخص الرسالة

الاســــــــــم: أديو عيسى أديمولا

عنوان الرسالة: تقويم المعادلات الرياضية التجريبية لخواص الضغط والحجم والحرارة لزيت الخام النيجيري .

التخصــــــص: هندسة البترول

تاريخ التخــرج: يناير 2005م

تقوم هذه الدراسة بعرض نتائج تقويم وتحديث أو إعادة حساب المعاملات لمعظم المعادلات الرياضية التجريبية للضغط والحجم والحرارة المتداولة في حساب كل من ضغط التشبع، ونسبة الغاز المذاب إلى الزيت، ومعامل الحجم التكويني للزيت عند ضغط التشبع، ولزوجة الزيت المشبع بالغاز ولزوجة الزيت الخالي من الغاز لمجموعات من بيانات الضغط والحجم والحرارة جمعت من مناطق مختلفة من جمهورية نيجيريا، و استحداث نماذج شبكات عصبية رياضية لجميع الخواص الخمسة السابقة الذكر للضغط والحجم والحرارة. كما قورنت أداء المعادلات الرياضية التجريبية باستخدام الأدوات الإحصائية والبيانية للتعرف على أفضل المعادلات الرياضية. وأيضا تم مقارنة أداء المعادلات الرياضية التجريبية مع نماذج الشبكات العصبية الرياضية.

وأظهرت هذه الدراسة أن النتائج تكون أكثر دقة عندما يعاد حساب المعاملات الرياضية التجريبية ببيانات المنطقة الجغرافية المدروسة. ويوضح هذا أن استخدام نيجيريا للمعادلات الرياضية التجريبية من منطقة أخرى غير مثالية. وأن النتائج المتحصل عليها من استخدام نماذج الشبكات العصبية الرياضية هي الأفضل لكل الخواص التي تمت دراستها.

درجة ماجستير العلوم في هندسة البترول

جامعة الملك فهد للبترول والمعادن

الظهران- المملكة العربية السعودية

يناير 2005م

ACKNOWLEDGMENT

All praise, thanks and adorations are due to Allah (SWT), the Lord of incomparable Majesty. Whatever He gives nobody can withhold and whatever He withholds nobody can give. He is the source of all strength and wisdom, the giver of success and to Him ultimately everything returns. May His peace and blessing be on the Prophet Muhammad, his household, his companions and all those who are rightly guided till this world cease to exist.

I wish to express my profound appreciation to Prof. Muhammad Ali Al-Marhoun who served as my thesis advisor for his relentless effort, advice, and guidance. I wish also to thank the other members of my thesis committee Dr. Hasan Yousef Al-Yousef and Dr. El-Sayed Ahmed Osman for their assistance. My thanks also go to Dr. Sidqi Ahmad Abu-Khamsin, the Chairman, Petroleum Engineering Department.

I will also like to thank all the faculties and staff in the Department of Petroleum Engineering, KFUPM for their hospitality.

Besides, I also wish to acknowledge the patience, courage and understanding of my wife and children throughout my staying away from them in the course of this study, may Allah reward them abundantly.

I cannot but to be grateful to the Petroleum Resources Department, Ministry of Petroleum Resources, Lagos, Nigeria for the authorization given for the release of the data used in this study. In the same vain, I thank Dr. Saka Matemilola for his supports. I also thank my mother, brothers and sisters for their moral supports. I acknowledge the efforts of my deceased father, for his support and ever useful advice. May Allah forgive him.

Finally, I thank all my friends in Saudi Arabia and in Nigeria for their supports.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

Introduction

Pressure-Volume Temperature (PVT) analysis is the study of the changes in volume of a fluid(s) as function of pressure and temperature. The essence of PVT analysis is to simulate what takes place in the reservoir and at the surface during production and provide vital information about physical and thermodynamic behavior of the reservoir fluids. An accurate understanding of reservoir fluid PVT properties forms the basis of reservoir simulations, recovery estimates, well completion and facility design decisions, pipeline flow assurance choices, production optimization strategies - practically all aspects of both a field's initial development and subsequent operation. The PVT data analysis is often used in predicting future performance, design of experiments and fluid handling equipment, calculation of oil and gas recovery, design of future EOR schemes and optimum design of production and surface facilities. The calculation of reserves in an oil reservoir and the determination of its performance and economics requires a good knowledge of the fluids' physical properties. Bubblepoint pressure, Solution GOR, Oil FVF at bubblepoint and compressibility are of primary importance in material balance calculation, whereas viscosity plays an important role in production test interpretation and in well problem analysis.

Ideally, the laboratory measurements of PVT properties are the primary source of PVT data determined from laboratory studies on samples collected from the bottom of the wellbore or from the surface. Such experimental data are however not always available because of one or more of such reasons: a) samples collected are not reliable, b) samples have not been taken because of cost saving, c) PVT analyses are not available when data are needed, this situation often occurs in production-test interpretation in exploration wells.

However, in the absence of such tests the use of correlations provides the only viable option for the prediction of PVT properties for field applications. Correlations are also useful as a check against laboratory results, in making estimates for experimental design and in generalization of properties.

In Nigeria, there has never been a comprehensive study of PVT parameters and subsequent development of PVT correlations of black oils for Nigerian crudes. Most of the petroleum industries in Nigeria rely on Standing, Vasquez and Beggs correlations for the prediction of PVT parameters. Therefore, it is most important to develop reliable correlations to predict PVT properties whenever needed.

1.1 Problem Statement

The use of Standing and Vasquez and Beggs correlations for the estimation of PVT properties for Nigerian crude oil is undoubtedly erroneous not only owing to low accuracy of the correlations but the correlations are mostly applicable to fluids having exact or similar nature to those from which the correlations were derived. Its application to predict PVT parameters of reservoir fluids from other regions can result in considerable inaccuracies when used outside the range of validity. The most relevant factor influencing the PVT properties of any reservoir fluid is the conditions under which it was formed. This determines the value of different volatile and heavy hydrocarbon compounds that constitute the oil. Therefore, it is difficult if not impossible to obtain the same accurate results through empirical correlations for different oil samples having different physical and chemical properties. As a result, the best PVT correlations are the ones developed for fluids of regional characteristics.

1.2 Objectives

The main objectives of this study are as follows:

1. To evaluate the most popular PVT correlations against a set of Nigerian PVT data and to recommend the best correlations for Nigeria crude oils.
2. To improve the performance of the most popular correlations by recalculating their coefficients using regression analysis.

3. To develop new correlations using neural network models for PVT properties using Nigerian data.

1.3 Approach

Statistical and graphical error analysis will be used as the criteria for the evaluation in this study. Existing correlations will be applied to Nigeria data set and error analysis will be performed based on a comparison of the predicted value with the original experimental value.

1.4 Nigeria Oil Production

Oil was discovered in Nigeria in 1956 at Oloibiri in the Niger delta after half a century of exploration. The discovery was made by SHELL-BP. Nigeria joined the ranks of oil producers in 1958 when its first oil field came on stream producing 5,100 bpd. Figure 1-1 is the map of oil producing area showing oil fields, cities and oil terminals.

As of today, Nigeria's estimated proven oil reserves range from 24 billion to 31.5 billion barrels. Also, Nigeria has an estimated 124 trillion cubic feet (tcf) of proven natural gas reserves (10th largest in the world) with estimates of associated and non-associated gas being as high as 300 tcf [1]. The majority of these reserves are found along the country's coastal Niger River Delta, but new reserves have been discovered in deeper waters offshore Nigeria. The majority of the oil lies in about 250 fields. At least 200 other fields exist contain undisclosed reserves.

Nigerian crude oil production averaged 2.118 million barrels per day in 2002. [2]. Nigeria's crude oil reserves have gravities ranging from 21˚API to 45˚API. Nigeria's main export crude blends are Bonny Light (37 ˚API) and Forcados (31˚API). Averagely Nigeria crude oil is light (35 ˚API or higher) and sweet (low sulfur content). Figure 1-2 shows the annual crude oil production in Nigeria from 1980-2002.

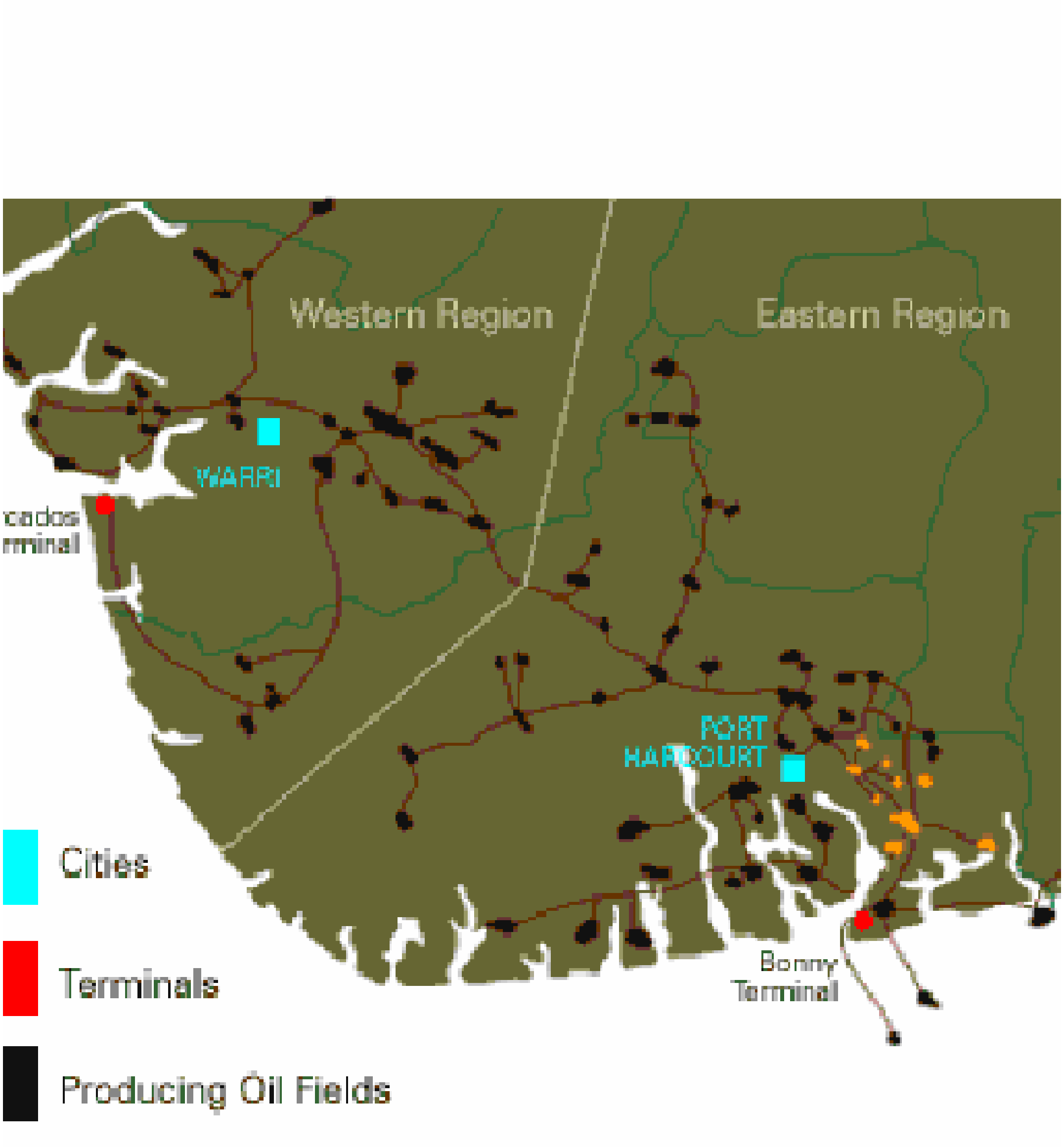

Figure 1-1 Map of Niger Delta Showing Oil Fields [1]

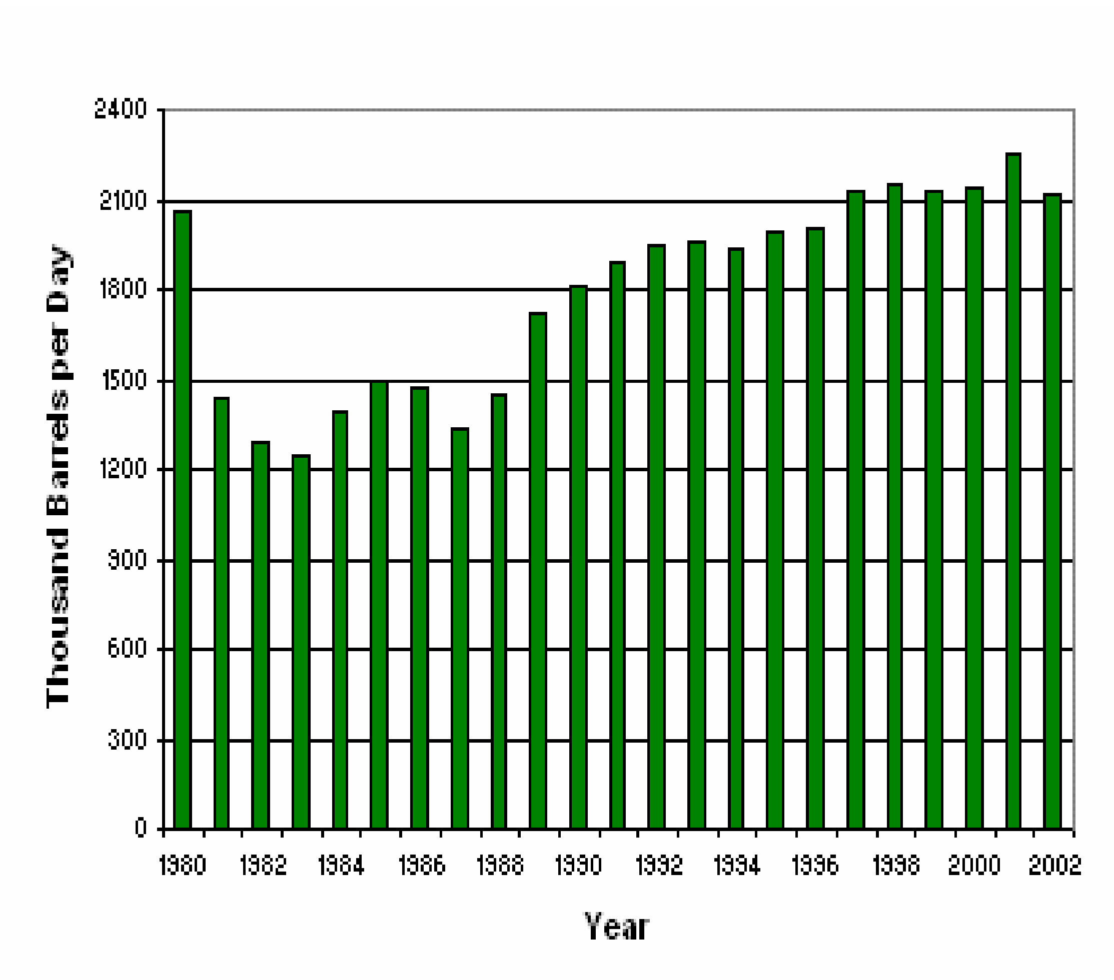

Figure 1-2 Crude Oil Production, 1980-2002 [2]

Chapter 2

Literature Review

In this section, some of the existing correlations will be reviewed. The PVT properties of interest include bubblepoint pressure (Pb), solution gas-oil ratio (GOR), oil formation volume factor at bubblepoint (FVF), Oil viscosity at bubblepoint and dead-oil viscosity.

2.1 Bubblepoint Pressure

Bubblepoint pressure is the pressure at which the first bubble of gas evolves. Bubblepoint pressure is empirically correlated as a function of solution GOR, gas density, oil density, and temperature.

2.1.1 Standing (1947) [3]

The most widely used bubblepoint pressure correlation was developed by Standing [3]. He developed a chart for bubblepoint pressure calculation. His chart was based on data from a limited geographical location and made no corrections for oil type or non-hydrocarbon contents. He used 105 experimental data points from a series of 22 different crude oil/natural gas mixtures from Californian oil fields. The ranges of the data are given in Table. 2-1 and the chart is shown in Figure 2-1. The chart was later developed into an equation of the form shown in appendix B. Standing reported an average percent relative error of 4.8%.

2.1.2 Lasater (1958) [4]

In the same vein, Lasater [4] developed a new correlation for the determination of bubblepoint pressure for black oil systems using 158 experimentally determined bubblepoint pressure of 137 independent crude oil systems from US, Canada and South America. The ranges of the data are given in Table.2-2. Lasater reported an average absolute error of 3.8%. The correlation is presented in form of a chart as shown in Figure 2-2.

2.1.3 Vasquez and Beggs (1980) [5]

Vasquez and Beggs [5] correlation for bubblepoint pressure was based on mathematical manipulation of their solution GOR correlation which was developed using 5008 data points taken from 600 laboratory PVT analyses from various fields all over the world. Though they claim using 5008 data points in the published paper but the original work contained in Vasquez thesis [6] shows only 259 data points and there are 4 points repeated. The ranges of the data reported in Vasquez thesis are given in Table 2-3.

2.1.4 Glaso (1980) [7]

Also, Glaso [7] developed a correlation and a nomograph for the prediction of bubblepoint pressure. He used data based on 45 oils samples from North Sea crude. The ranges of the data are given in Table. 2-4. Glaso reported an average absolute percent relative error of estimated saturation pressures from experimental values was 1.28 in the pressure range of 150 to 7,000 psig and 0.7 in the pressure range of 2,000 to 7,000 psig. The correlation is shown in appendix B and the nomograph is shown in Figure 2-3.

2.1.5 Al- Marhoun (1988) [8]

Al-Marhoun [8] developed an empirical correlation for determining bubblepoint pressure using 160 experimentally obtained data points from the PVT analyses of 69 bottomhole fluid samples from 69 Middle East oil reservoirs. The ranges of the data are given in Table. 2-5. The reported average relative and absolute relative error are 0.03% and 3.66% respectively. On the basis of the mathematically developed PVT correlations, he also presented a graphical method for estimating bubblepoint pressure in the form of a nomograph nomograph is shown in Figure 2-4.

2.1.6 Dokla and Osman (1992) [9]

Dokla and Osman [9] presented a correlation for predicting bubblepoint pressure based on the correlation developed by Al- Marhoun (1988). The correlation was developed using 51 bottomhole samples of United Arab Emirate (UAE). The ranges of the data are given in Table. 2-6. The average absolute relative error was 7.61%. Dokla and Osman correlation is the same as Al-Marhoun (1988) correlation with different constants. They also presented a nomograph for estimating bubblepoint pressure as shown in Figure 2-5.

Table 2-1 Data Parameters and Ranges for Standing [3]

PVT Property	Range
Number of data point	105
Oil FVF at bubblepoint, BBL/STB	1.024-2.15
Bubblepoint pressure (psia)	130-7000
Solution GOR, (scf/stb)	20-1425
Reservoir temperature (˚F)	100-258
Oil API gravity, ˚API	16.5-63.8
Gas relative density (air=1)	0.59-0.95

Example

Required:

Bubble-point pressure at 200 °F of a liquid having a gas-oil-ratio of 350 CFB, a gas gravity of 0.70, and a tank-oil gravity of 30 °F.

Procedure:

Starting at the left side of the chart, proceed horizontally along the 350 CFB line to a gas gravity of 0.70. From this point drop vertically to the 30°API line. Proceed horizontally from the tank-oil gravity scale to the 200 °F line. The required pressure is found to be 1930 PSIA.

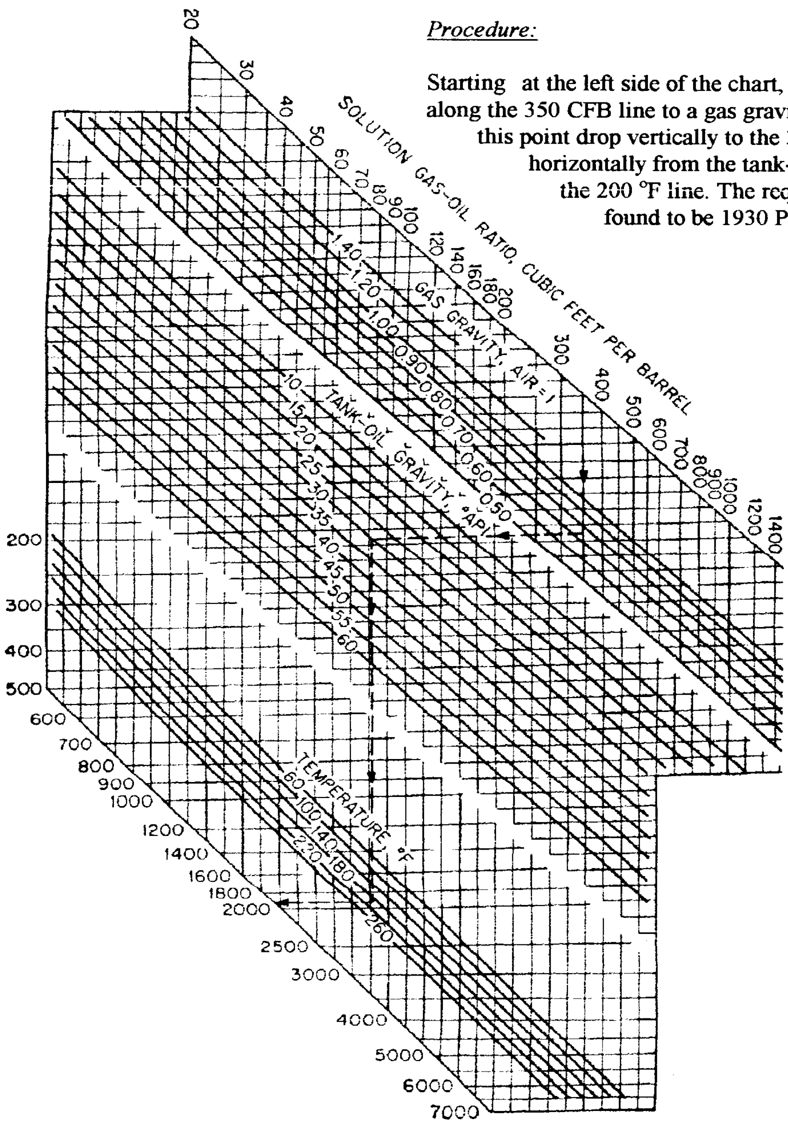

Figure 2-1 Chart for Calculating Pb by Standing [3]

Table 2-2 Data Parameters and Ranges for Lasater [4]

PVT Property	Range
Number of data point	158
Bubblepoint pressure (psia)	48-5780
Solution GOR, (scf/stb)	3-2905
Reservoir temperature (˚F)	82-272
Oil API gravity, ˚API	17.9-51.1
Gas relative density (air=1)	0.574-1.223
Separator pressure, (psia)	15-605
Separator temperature, (˚F)	34-106

Example

Required:

Bubble-point pressure at 200 °F of a liquid having a gas-oil-ratio of 500 CFB, a gas gravity of 0..8, and a tank-oil gravity of 30 °F.

Procedure:

Starting at the left side of the chart, proceed horizontally along the 500 CFB line to an oil gravity of 30° API. Now drop vertically to the 200° F line. Now rise vertically to the 0.8 gas gravity line. The required pressure is read horizontally at the right- 2625 PSIA.

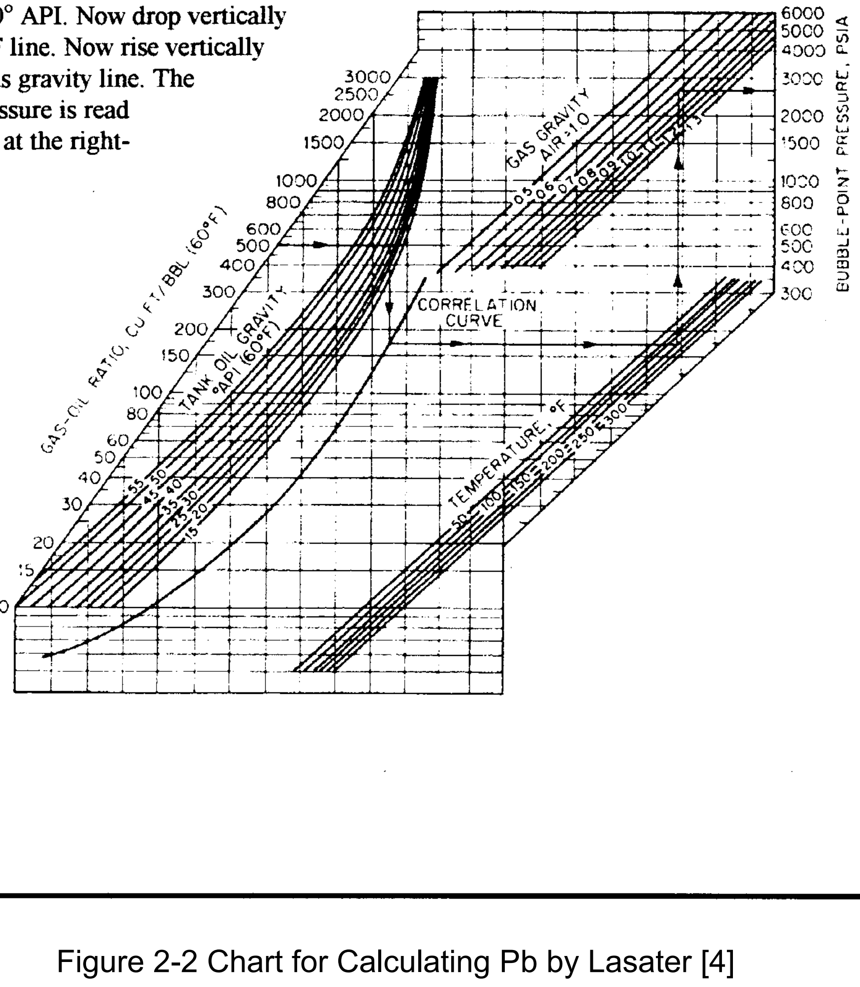

Figure 2-2 Chart for Calculating Pb by Lasater [4]

Table 2-3 Data Parameters and Ranges for Vasquez and Beggs [5]

PVT Property	Range
Number of data point	6004
Oil FVF at bubblepoint, bbl/stb	1.028-2.226
Bubblepoint pressure (psia)	15-6055
Solution GOR, (scf/stb)	0-2199
Reservoir temperature (˚F)	75-294
Oil API gravity, ˚API	15.3-59.5
Gas relative density (air=1)	0.511-1.351

Table 2-4 Data Parameters and Ranges for Glaso [7]

PVT Property	Range
Number of data point	45
Oil FVF at bubblepoint, bbl/stb	1.087-2.588
Bubblepoint pressure (psia)	165-7142
Solution GOR, (scf/stb)	90-2637
Reservoir temperature (˚F)	80-280
Oil API gravity, ˚API	22.3-48.1
Gas relative density (air=1)	0.65-1.276

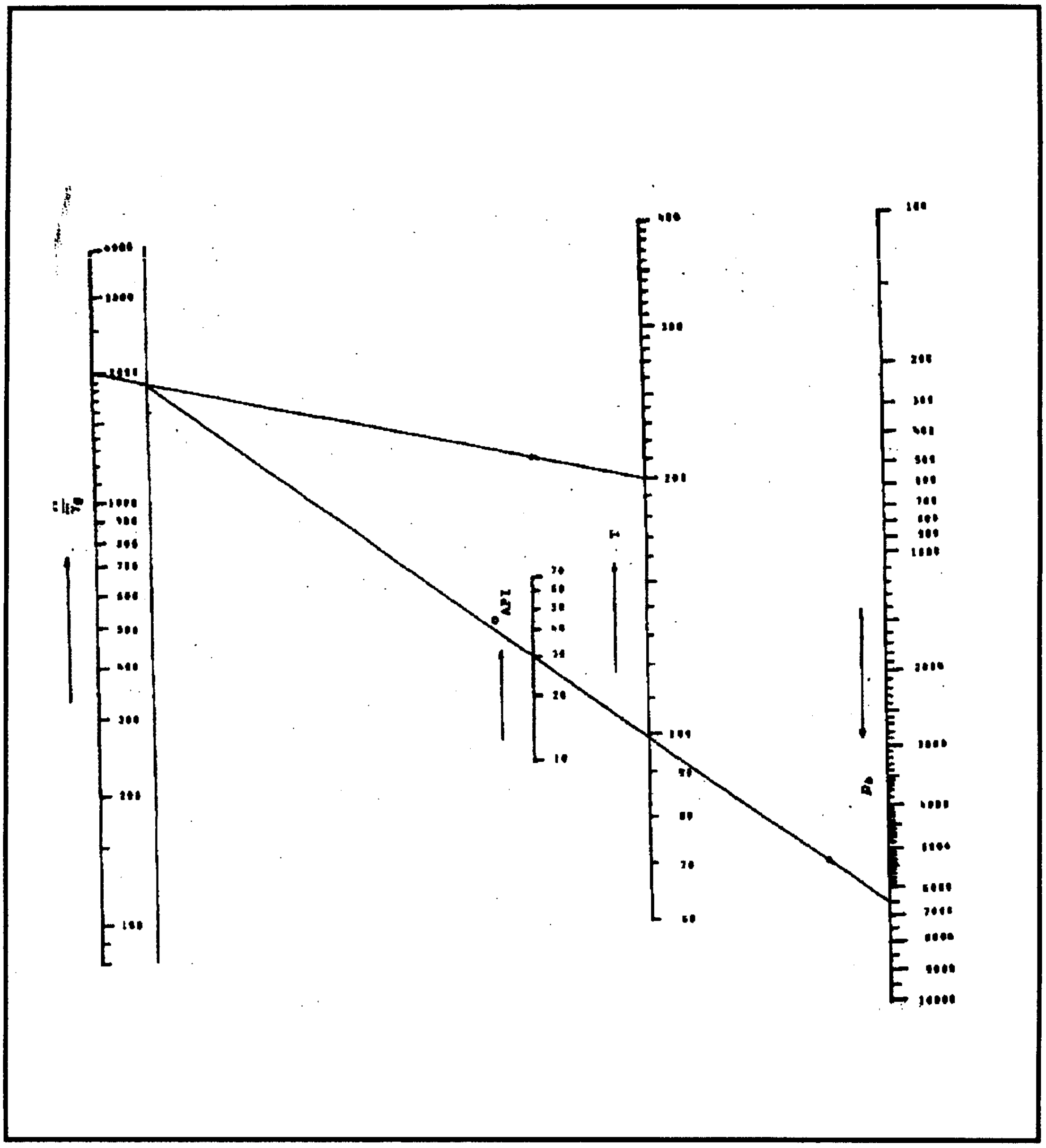

Figure 2-3 Nomograph for Calculating Pb by Glaso [7]

Table 2-5 Data Parameters and Ranges for Al-Marhoun [8]

PVT Property	Range
Number of data point	160
Oil FVF at bubblepoint, bbl/stb	1.032-1.997
Bubblepoint pressure (psia)	130-3573
Solution GOR, (scf/stb)	26-1602
Reservoir temperature (˚F)	74-240
Oil API gravity, ˚API	19.4-44.6
Gas relative density (air=1)	0.752-1.367
CO_2 in surface gases, mol%	0.00-16.13
Nitrogen in surface gases, mol%	0.00-3.89
H_2S in surface gases, mol%	0.00-16.13

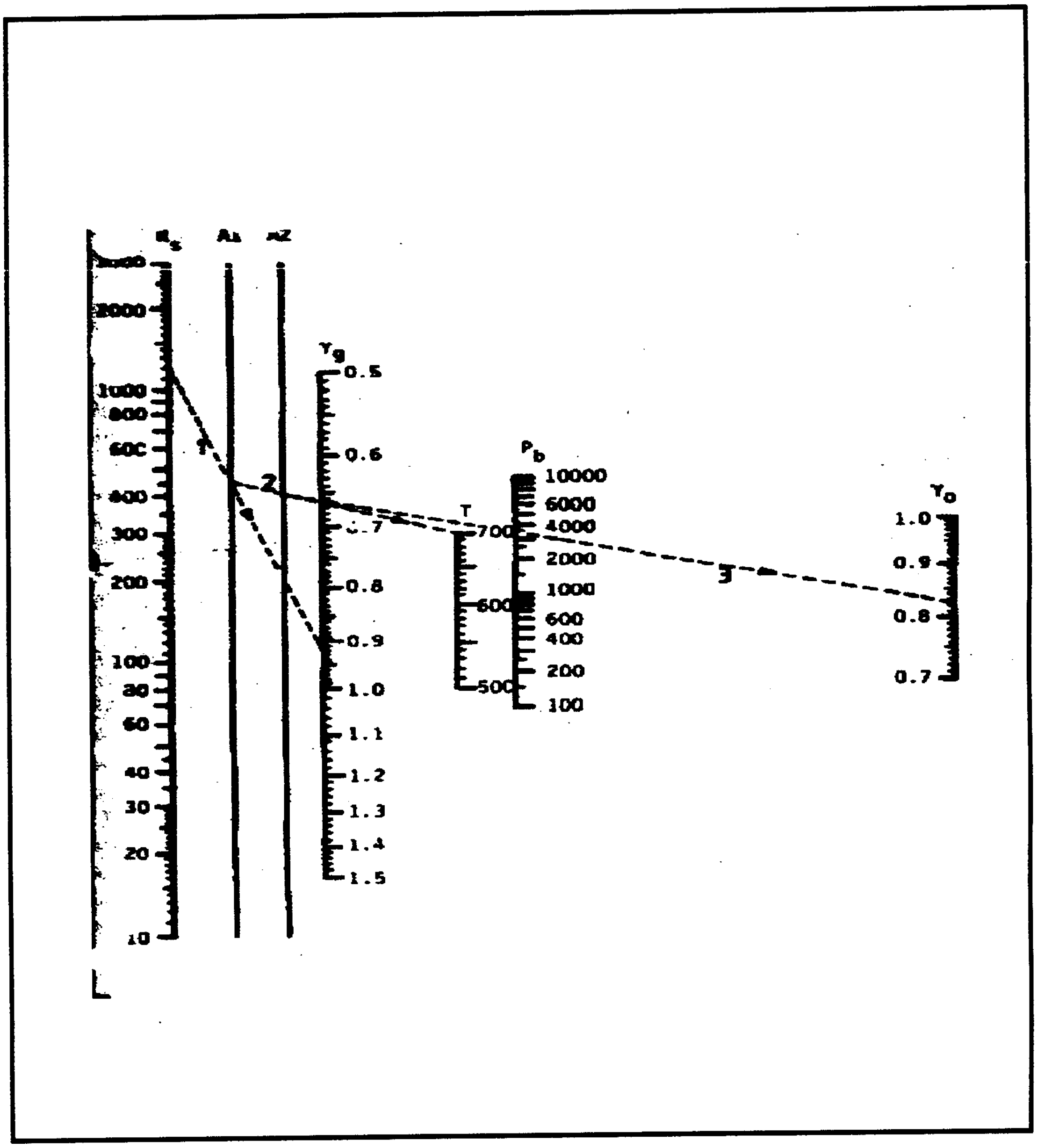

Figure 2-4 Nomograph for Calculating Pb by Al-Marhoun (1988) [8]

Table 2-6 Data Parameters and Ranges for Dokla and Osman [9]

PVT Property	Range
Number of data point	51
Oil FVF at bubblepoint, bbl/stb	1.216-2.493
Bubblepoint pressure (psia)	590-4640
Solution GOR, (scf/stb)	181-2266
Reservoir temperature (˚F)	190-275
Oil API gravity, ˚API	28.2-40.3
Gas relative density (air=1)	0.798-1.29
CO_2 in surface gases, mol%	0.37-8.9
Nitrogen in surface gases, mol%	0.1-1.85
H_2S in surface gases, mol%	0.00-6.02

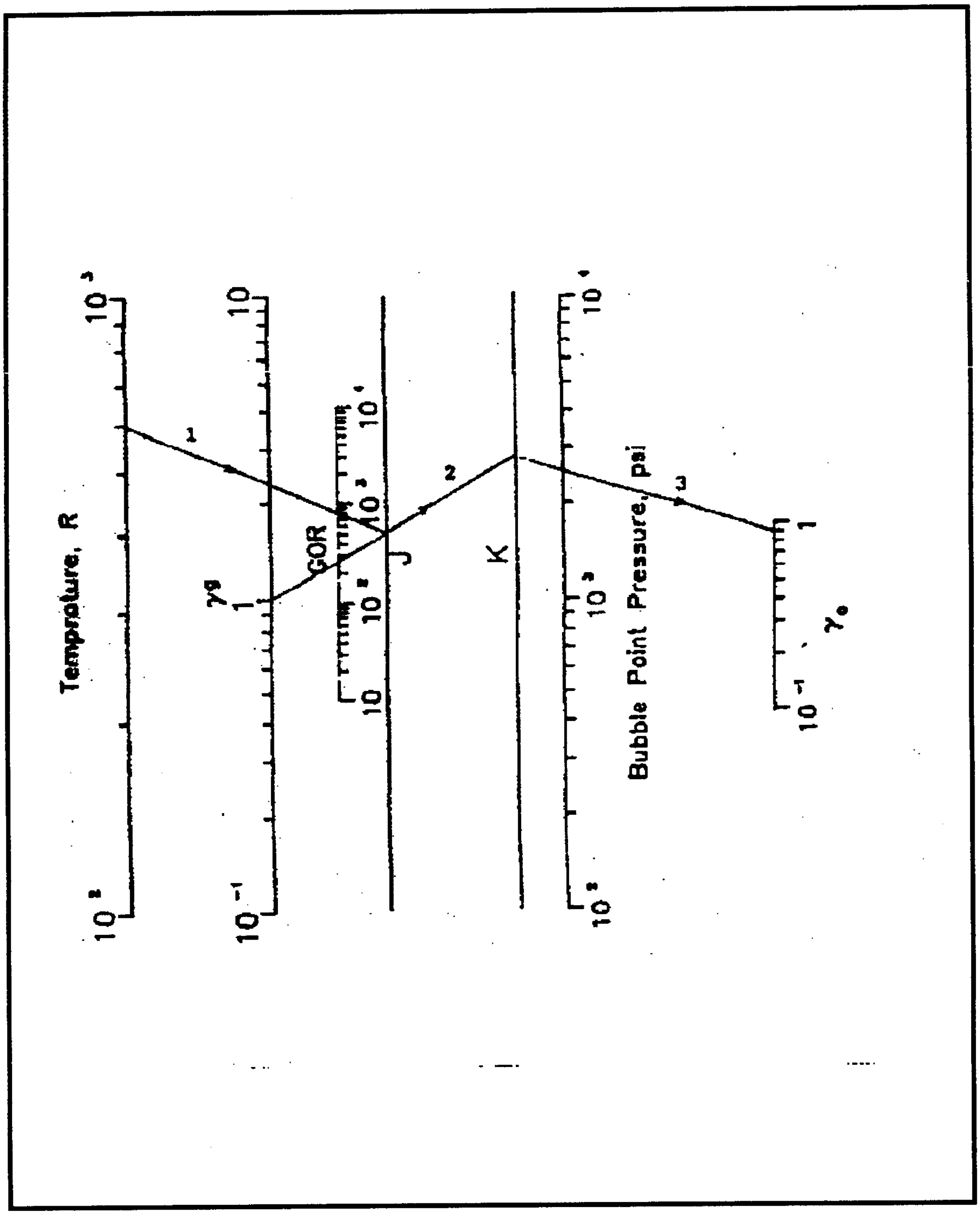

Figure 2-5 Nomograph for Calculating Pb by Dokla and Osman [9]

2.1.7 Petrosky and Farshad (1993) [10]

Petrosky and Farshad [10] developed a bubblepoint pressure correlation for the Gulf of Mexico Crude Oils using 81 laboratory PVT analyses from more than 32 reservoirs located offshore Texas and Louisiana. The ranges of the data are given in Table 2-7. The bubblepoint pressure correlation predicts measured bubblepoint pressures with average relative and absolute errors of -0.17% and 3.28% respectively.

2.1.8 Omar and Todd (1993) [11]

Omar and Todd [11] developed a correlation for calculating bubblepoint pressure using data from Malaysian offshore oil fields at the South China Sea. The ranges of the data are given in Table 2-8 and the average absolute error is 7.17%.

2.2 Solution Gas Oil Ratio

Solution GOR is the ratio of gas evolves from solution to oil produced at stock tank. It is defined as the amount of gas dissolved in 1 STB of oil. The solution GOR correlation is basically the mathematical solution of Rs from Pb correlations except for Vasquez and Beggs.

2.2.1 Standing (1947) [3]

Standing [3] correlation for solution GOR is rearrangement of his correlation for the estimation of bubblepoint pressure.

2.2.2 Vasquez and Beggs (1980) [5]

Vasquez and Beggs [5] developed a general relationship for solution GOR using 5008 data points taken from 600 laboratory PVT analyses from various fields all over the world as reported in 2.1.3.

2.2.3 Al-Marhoun (1988) [8]

Al-Marhoun [8] correlation for solution GOR is rearrangement of his bubblepoint pressure correlation.

2.3 Oil Formation Volume Factor at Pb

Oil formation volume factor at bubblepoint is the volume at reservoir conditions occupied by one stock tank barrel of oil plus its solution gas. This factor is used for estimating the shrinkage of oil liquid volume as oil is produced from the reservoir to the surface. Oil FVF at bubblepoint has been estimated as a function of GOR, gas density, oil density, and reservoir temperature. Below are the most popular empirical correlations in the literature to predict oil FVF at bubblepoint.

2.3.1 Standing (1947) [3]

Standing [3] developed a chart for estimating oil FVF at bubblepoint for Californian oils. His chart was based on the same 105 experimental data points presented in Table 2-1. The chart is as shown in Figure 2-6 and later presented in form of an equation presented in the Appendix B. However, the correlation does not conform to the limiting condition at GOR =0 and temperature =60˚F, the expected value should be 1 but this correlation gives 0.99724.

2.3.2 Vasquez and Beggs (1980) [5]

Vasquez and Beggs [5] developed a general relationship estimating oil FVF at bubblepoint using 5008 data points from various field all over the world. The same data was used to develop correlation for solution GOR and shown in Table 2-3. The correlation is developed with different coefficients for API≤ 30 and API>30, therefore, there will be a discontinuity at API=30. Besides, the negative coefficient value for a_3 when API≤ 30 and positive value for a_3 when API>30 for the same crude shows inconsistency in the correlation since the trend of each independent parameter should remain the same at high and low API. However, the correlation meets the condition for the oil FVF of 1 at 60˚F and atmospheric pressure (GOR=0).

2.3.3 Glaso (1980) [7]

Glaso [7] developed a correlation for the prediction of oil FVF at bubblepoint. He used limited data based on 45 oils samples from North Sea crude. PVT data and oil samples from North Sea reservoirs were collected from wells in the region 56 to 62ºN. Other PVT data analyzed in the paper are from the Middle East, Algeria, and several areas in the US. The same data was used to develop a correlation for bubblepoint pressure and shown in Table 2-4. The correlation was developed for North Sea oils, based on similar work by Standing. The paraffinicity characterization factor is assumed to be constant within a specific region. The correlation does not conform to the limiting condition at GOR=0 and temperature=60˚F, the expected value should be 1 but the correlation gives 1.000001319. The standard deviation of error in estimating oil FVF at bubblepoint was 2. 18%. The correlation was also presented in a nomograph form as shown in Figure 2-7.

2.3.4 Al-Marhoun (1988) [8]

Al-Marhoun [8] developed a correlation for estimating oil FVF at bubblepoint for Middle East oils using nonlinear multiple regression analysis and a trial-and-error method based on the 160 experimentally determined data points. The same data set was used for developing bubblepoint pressure in 1988. The range of the data is shown in Table 2-5 and the average absolute relative error was 0.88%. The correlation is as shown in Appendix B. The correlation does not conform to the limiting condition at GOR=0 and temperature=60˚F, the expected value should be 1 but the correlation gives 0.9458. The correlation was also presented in form of nomograph as shown in Figure 2-8.

2.3.5 Al-Marhoun (1992) [12]

Al-Marhoun [12] developed another correlation for estimating oil FVF at bubblepoint using 4012 experimentally obtained data from all over the world mostly from Middle East and Canadian oil fields. The range of the data is shown in Table 2-9. The equation was developed using non-linear regression. The correlation meets the condition for the oil FVF of 1 at 60˚F and atmospheric pressure where GOR is zero. The absolute relative error was 0.28%.

Table 2-7 Data Parameters and Ranges for Petrosky and Farshad [10]

PVT Property	Range
Number of data point	90
Oil FVF at bubblepoint, bbl/stb	1.1178-1.6229
Bubblepoint pressure (psia)	1547-6523
Solution GOR, (scf/stb)	217-1406
Reservoir temperature (˚F)	114-288
Oil API gravity, ˚API	16.3-45.0
Gas relative density (air=1)	0.578-0.852
CO_2 in surface gases, mol%	0.00-0.8519
Nitrogen in surface gases, mol%	0.00-0.79

Table 2-8 Data Parameters and Ranges for Omar and Todd [11]

PVT Property	Range
Number of data point	93
Oil FVF at bubblepoint, bbl/stb	1.085-1.954
Bubblepoint pressure (psia)	790-3851
Solution GOR, (scf/stb)	142-144
Reservoir temperature (˚F)	125.0-280.0
Oil API gravity, ˚API	26.6-53.2
Separator temperature, (˚F)	70.0-160.0
Separator pressure, (psia)	75-500
CO_2 in surface gases, mol%	0.00-35.0
Nitrogen in surface gases, mol%	0.00-1.15
H_2S in surface gases, mol%	traces

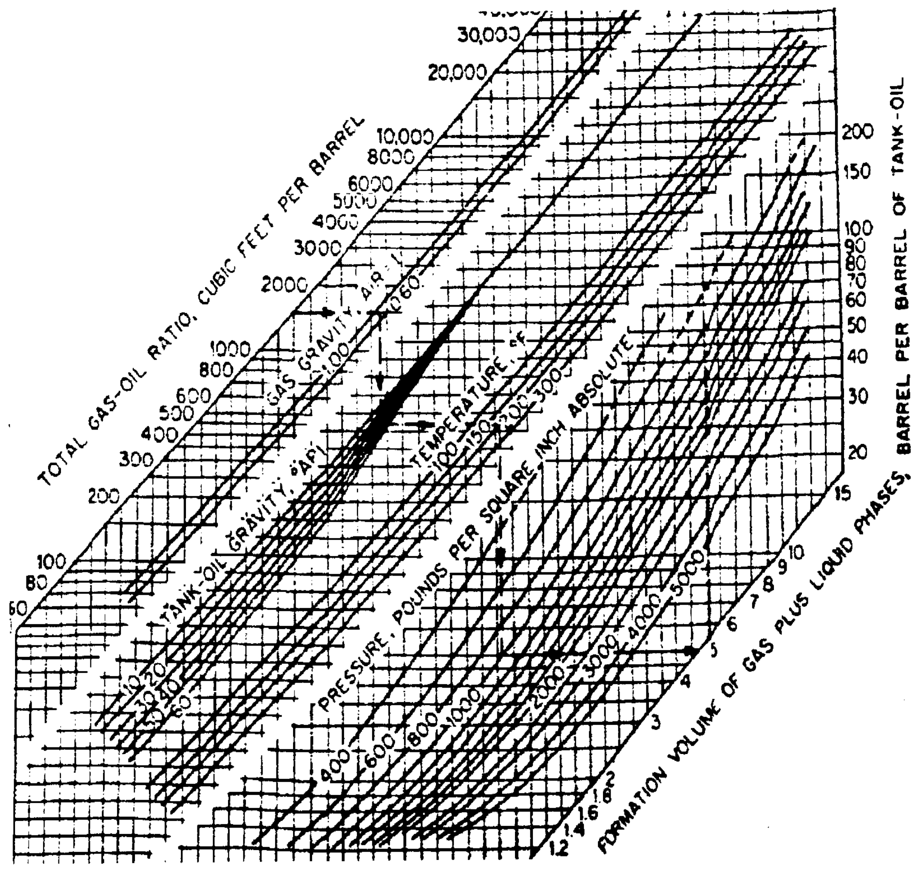

Figure 2-6 Chart for Calculating Oil FVF at Pb by Standing [3]

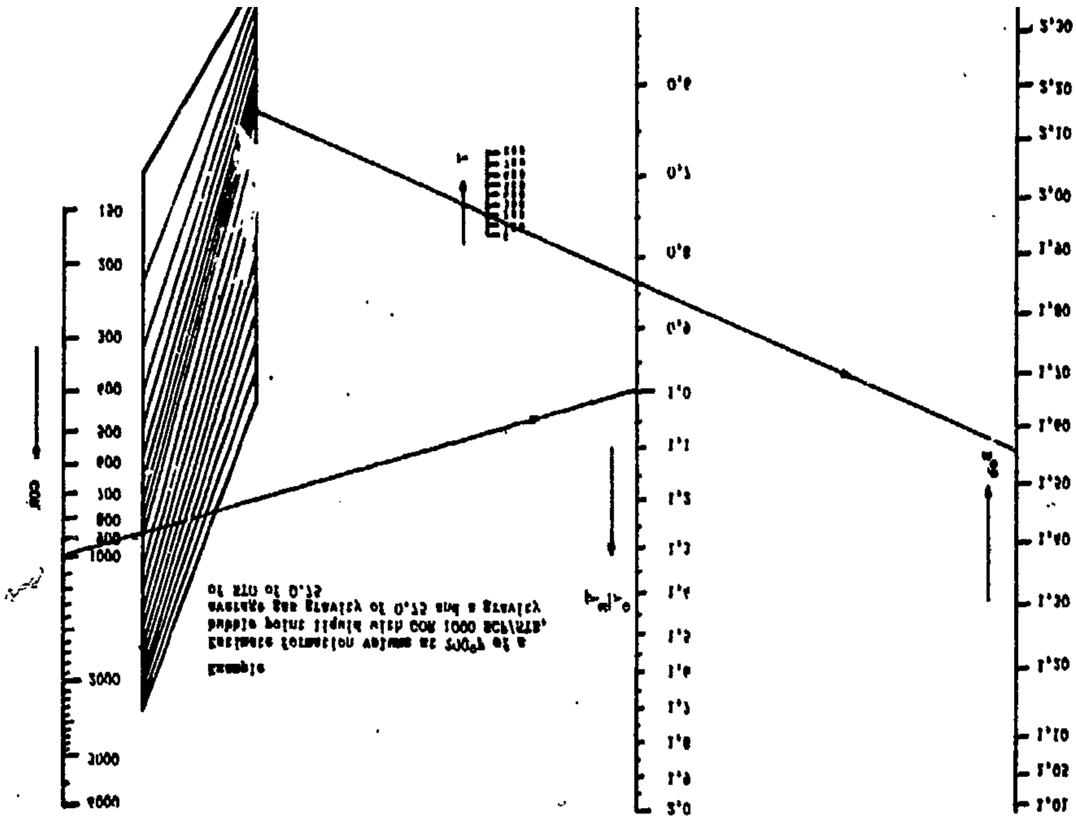

Figure 2-7 Nomograph for Calculating Oil FVF at Pb by Glaso (1980) [7]

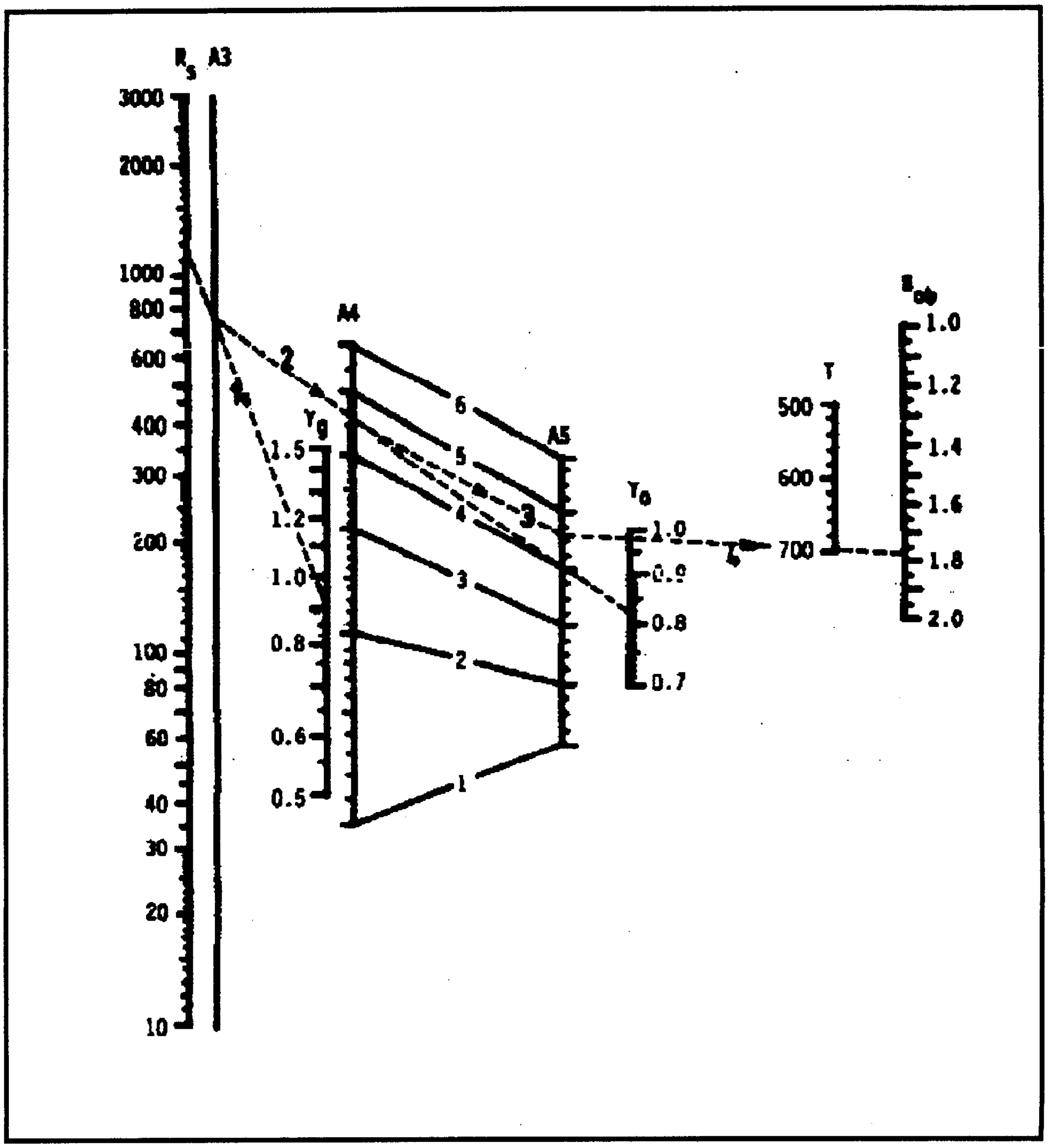

Figure 2-8 Nomograph for Calculating Oil FVF at Pb by Al-Marhoun (1988) [8]

Table 2-9 Data Parameters and Ranges for al-Marhoun (1992)

PVT Property	Range
Number of data point	4012
Oil FVF at bubblepoint, bbl/stb	1.010-2.960
Bubblepoint pressure (psia)	15-6641
Solution GOR, (scf/stb)	0-3265
Reservoir temperature (˚F)	75-300
Oil API gravity, ˚API	9.5-55.9
Gas relative density, Air=1	0.575-2.510

2.3.6 Petrosky and Farshad (1993) [10]

Petrosky and Farshad [10] presented an empirical correlation similar to Standing correlation with minor modifications for estimating oil FVF at bubblepoint for the Gulf of Mexico crude oils. They used a total of 90 data points obtained from 81 laboratory PVT analysis from crude oils extracted from reservoirs offshore Texas and Louisiana. The same data was used for developing bubblepoint pressure. The range of the data is shown in Table 2-7 and the average absolute error was 0.64%. The correlation does not conform to the limiting condition at GOR=0 and temperature=60˚F, the correlation gives 1.01215 rather than 1.

2.3.7 Omar and Todd (1993) [11]

Omar and Todd [11] developed a correlation for calculating oil FVF at bubblepoint using data from Malaysian offshore oil fields at the South China Sea. Both linear and non-linear regressions were used. The average absolute error was 1.44%.

2.4 Oil viscosity at bubblepoint

Viscosity is defined as the internal resistance of the fluid to flow. Viscosity of crude oil decreases when saturated with gas under pressure. The amount of decrease depending principally on pressure, reservoir temperature and the characteristics of the oil and gas.

2.4.1 Chew and Connally (1959) [13]

Chew and Connally [13] presented a graphical correlation to adjust the dead oil viscosity according to the gas solubility at saturation pressure. The correlation was developed using viscosity data of a total of 457 crude oil samples. The data were obtained with rolling ball-type viscometer. The samples used were obtained from producing areas of US, Canada and South America.

2.4.2 Beggs and Robinson (1975) [14]

Beggs and Robinson [14] developed an empirical correlation for determining the oil viscosity at bubblepoint. The correlation was developed by analyzing 600 oil systems utilizing 2073 oil viscosity measurements. The range of the data used is given in Table 2-10.

2.4.3 Khan, Al-Marhoun, Abu-Khamsin & Duffuaa (1987) [15]

Khan, Al-Marhoun, Abu-Khamsin & Duffuaa [15] developed a correlation for estimating oil viscosity at bubblepoint based on 150 data points taken from 75 bottom hole samples from 62 Saudi Arabian oil reservoirs data from Saudi Arabian crude oils. The ranges of the data are given in Table 2-11. The average absolute relative error was 12.148%.

2.4.4 Abu-Khamsin & Al-Marhoun (1991) [16]

Abu-Khamsin & Al-Marhoun [16] developed an oil viscosity at bubblepoint correlation based on the data for 62 Middle Eastern reservoirs. The data set contains a total of 459 points. The ranges of the data are given in Table 2-12. The average absolute relative error was 7.56%.

2.4.5 Labedi (1992) [17]

Labedi [17] developed a correlation for the light oil viscosity at bubblepoint. He used 91 viscosity data points obtained from PVT reports collected from Libya oil fields. Multiple-regression analysis was used to develop the correlation.

2.5 Dead-Oil Viscosity

Dead oil viscosity measures the oil's resistance to flow at atmospheric pressure (no gas in solution) and system temperature.

2.5.1 Beal (1946) [18]

Beal [18] developed a graphical correlation to estimate dead-oil viscosity. He used 753 oil samples. The ranges of the data are given in Table 2-13. He correlated oil API and temperature covering a range of $100-220^{\circ}F$. The average error is 24.2%. The correlation was presented in form of a chart as shown in Figure 2-9.

2.5.2 Beggs and Robinson (1975) [14]

Beggs and Robinson [14] used 600 oil systems to develop their correlation for dead oil viscosity. The ranges of the data are given in Table 2-14. An average error of -0.64% was reported.

2.5.3 Glaso (1980) [7]

The correlation was developed from experimental measurements of 26 crude oil samples within the range of $50-300^{\circ}F$ for the system temperature and $20.1-48.1^{\circ}$ for the API gravity of the crude.

Table 2-10 Data Parameters and Ranges for Beggs and Robinson [14]

PVT Property	Range
Number of data point	2073
Dead-oil viscosity, cp	NA
Pressure (psig)	0-5250
Solution GOR, (scf/stb)	20-20270
Reservoir temperature (˚F)	70-295
Oil API Gravity, ˚API	16-58

Table 2-11 Data Parameters and Ranges for Khan et al [15]

PVT Property	Range
Number of data point	150
Bubblepoint viscosity,cp	0.13-17.9
Oil viscosity above bubblepoint, cp	0.13-71.0
Oil viscosity below bubblepoint, cp	0.13-77.4
Bubblepoint pressure (psia)	107-4315
Solution GOR, (scf/stb)	24-1901
Reservoir temperature (˚F)	75-240
Oil API gravity, ˚API	14.3-44.6
Gas relative density, air=1	0.752-1.367
CO_2 in surface gases, mol%	0.03-11.07
Nitrogen in surface gases, mol%	0.02-1.01
H_2S in surface gases, mol%	0.00-9.78

Table 2-12 Data Parameters and Ranges for Abu-Khamsin and Al-Marhoun [16]

PVT Property	Range
Number of data point	459
Bubblepoint viscosity,cp	0.105-17.65
Solution GOR, (scf/stb)	21-3001
Reservoir temperature (˚F)	74-240
Oil API gravity, ˚API	21-49
Gas relative density, air=1	0.525-1.588
Bubblepoint relative density	0.493-0.897

Table 2-13 Data Parameters and Ranges for Beal [18]

PVT Property	Range
Number of data point	753
Dead-oil viscosity,cp	0.865-155
Reservoir temperature (˚F)	100-220
Oil API gravity, ˚API	10.1-52.2

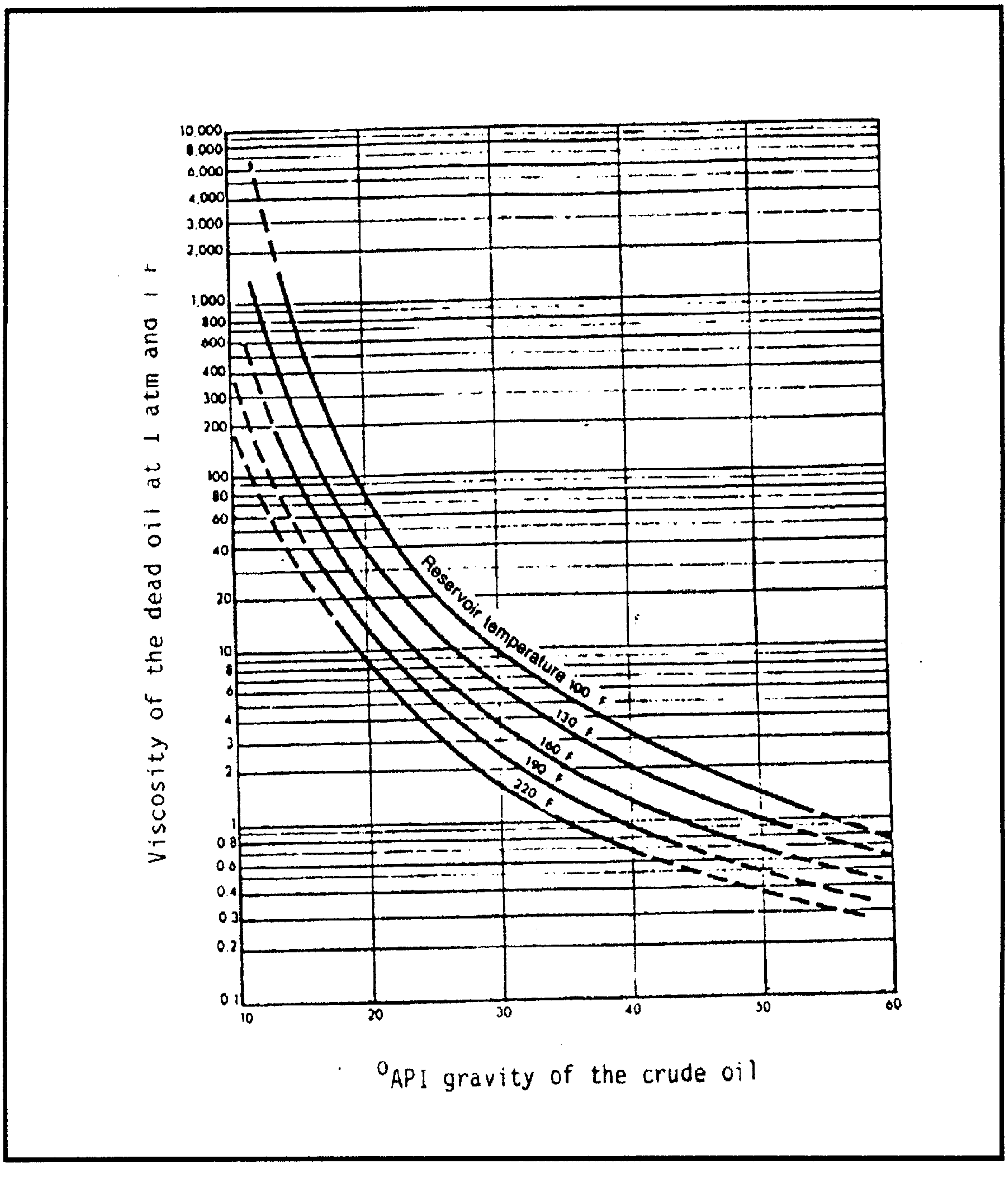

Figure 2-9 Chart for Calculating Dead-Oil Viscosity by Beal [18]

Table 2-14 Data Parameters and Ranges for Beggs and Robinson [14]

PVT Property	Range
Number of data point	460
Dead-oil viscosity,cp	NA
Reservoir temperature (˚F)	70-295
Oil API gravity, ˚API	16-58

Chapter 3

Data Acquisition

The data used in this study were obtained from analysis of 500 bottomhole samples from different Nigerian reservoirs. The experimentally obtained points are 2500 data points. The data were collected from various reservoirs/fields of different chemical compositions throughout Nigerian oil fields in the Niger-delta. Table 3-1 presents the description of data utilized in this study with a wide range of bubblepoint pressure, solution gas-oil ratio, reservoir temperature, oil formation volume factor at bubblepoint, oil viscosity at bubblepoint, dead oil viscosity, gas relative density, and API oil gravity. The number of data points used for bubblepoint pressure, solution gas-oil ratio, oil formation volume factor at bubblepoint is 2062, while the number of data points used for bubblepoint viscosity is 2024 and a dead-oil viscosity data points are 2011.

3.1 Data Screening

Physical Examination: all input parameters were examined in the light of physical PVT fluid properties behavior of typical petroleum fluids. Every row with any zero value is removed. All outrageous values were removed e.g oil FVF value of 0.6.

Outliers of a few observations that are not well fitted by the "best" available model are removed. In practice and in this study any observation with standardized residual greater than 2.5 in absolute value is a candidate for being an outlier. The outliers were removed and the model refitted.

The methodologies used to screen the data are:

1. The mean and standard deviation of each column of the data are computed.
2. Outliers are obtained by defining a set of limits off the mean (the difference between mean and the measured value).
3. Rows with outliers greater than 2.5 standard deviations are removed.

Table 3-1 Data Description for Nigerian Crude oil Used

PVT Property	Minimum	Maximum	Mean	Standard Deviation
Bubblepoint pressure psia	550	5984	3310.7	944.5
Solution GOR, scf/STB	30	1600	688.12	395.31
Oil FVF at bubblepoint, bbl/stb	1.04	2.19	1.36	0.23
Reservoir Temperature, ˚F	110	275	168.57	26.50
Oil ˚API gravity	14.01	56.50	30.84	8.38
Gas relative density, (air=1)	0.53	0.99	0.65	0.04
Oil viscosity at bubblepoint, cp	0.12	38.79	2.07	3.58
Dead-oil viscosity, cp	0.17	208.41	12.92	21.51
Oil relative density, 60/60F	0.75	0.97	0.87	0.05

Chapter 4

Correlations Evaluation

4.1 Bubblepoint Pressure

A search of the literature has identified a number of studies on the evaluation of existing correlations for more accurate estimation of bubblepoint pressure.

In 1983, Ostermann et al [19] evaluated published correlations for estimating bubblepoint pressure using Alaskan fluid data. PVT reports for 4 fields in the Cook Inlet Basin with 8 data points were used in the evaluation. They evaluated Standing, Vasquez and Beggs, Lasater and Glaso correlations. The result of their evaluation shows that Glaso correlation provided the most accurate prediction for the bubblepoint pressure using Alaskan crudes with a mean error of 1.6 and standard deviation of 4.9%.

Furthermore, in 1987, Saleh et al [20] published their work on the evaluation of empirical correlations for Egyptian oils. The samples used in their study are taken from different reservoir zones and from different oil fields. Besides, the laboratory analyses for these samples are not conducted in the same laboratory. Some of the analyzed samples are not in complete agreement with the approximate range of black oil properties. They evaluated Standing, Vasquez and Beggs, Lasater and Glaso correlations. They recommend the use of Glaso's bubblepoint correlation for Egyptian crude with average absolute percent relative error of 7.34 and standard deviation of 5.77.

In 1990, Sutton and Farshad [21] published an evaluation of the four correlations studied by Ostermann using Gulf of Mexico crude oils. They used 285 data points for gas saturated oil and 134 data points for under-saturated oil representing 31 different crude oils and natural gas systems. Standing, Vasquez and Beggs, Lasater and Glaso correlations were evaluated. The study shows that Glaso correlations for bubblepoint pressure provided the best result of all the correlations evaluated with average absolute relative error of 17.79%.

In 1996, Mahmood and Al-Marhoun [22] published their study on evaluation of bubblepoint pressure correlations for Pakistani crude oils. They used 166 data sets from 22 different crude samples for the evaluation. High errors were obtained for bubblepoint pressure. Standing, Lasater,Vasquez and Beggs, Glaso and Al-Marhoun (1988) were evaluated. Lasater (1958) and Al-Marhoun (1988) performed best with average absolute relative error of 31.31 and 31.50 respectively.

In 1999, Al-Shammasi [23] published a study on the evaluation of Standing, Al-Marhoun, Vasquez and Beggs, Glaso, Kartoatmodjo and Schmidt, Dokla and Osman, Farshad et al, Almehaideb, Lasater, Macary and El Batanoeney, Petrosky and Farshad, and Omar and Todd correlations for bubblepoint pressure using a total of 1243 data sets from 13 different published literature papers and Kuwait reservoirs. His study shows that Standing correlation has the least average absolute relative error of 20.685.

In 2004, Al-Marhoun [24] evaluated Standing, Vasquez and Beggs, and Al-Marhoun bubblepoint correlations using 530 data points obtained from Middle East crude oils. Al-Marhoun (1988) bubblepoint pressure correlation has the least average absolute error of 7.81.

The common approach of evaluating correlations by most authors is to select generally aclaimed and mostly used correlations and adapt it to a set of data. In this study, Standing, Glaso, Al-Marhoun, and Vasquez and Beggs correlations for bubblepoint pressure were evaluated using Nigerian data. Statistical error analysis was used to evaluate the performance of the correlations. The average percent relative error, maximum absolute percent relative error, minimum absolute percent relative error, average absolute percent relative error, root mean square, skewness and kurtosis were the major statistical parameters used as a comparative criteria for the testing of the evaluated correlations. The details of these statistical parameters were given in Appendix A. The statistical accuracy of bubblepoint pressure is shown in the Table 4-1.

Table 4-1 Statistical Accuracy of Pb

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Standing(1947)	5.67	14.24	0.0196	80.41	18.05	0.87	0.17	4.22
Glaso(1980)	-12.22	16.86	0.0012	86.45	21.39	0.87	0.53	6.14
Vasquez and Beggs(1980)	-8.64	16.6	0.0127	75.26	21.6	0.84	0.358	4.56
Al-Marhoun(1988)	-21.27	24.85	0.0076	70.98	30.30	0.86	0.32	3.51

Graphical analysis includes crossplot and histogram of relative errors. Crossplot is a plot of the measured value versus experimental value. A perfect correlation would plot as a straight line with a slope of 45º. The histogram of error distribution is a plot of frequency versus relative errors. This plot is used to determine the adequacy and even distribution of error of the correlation. A good correlation should follow a normal distribution.

From the Table 4-1 Standing (1947) correlation outperforms the rest of correlations studied with average percent relative and absolute errors of 5.67 and 14.24 respectively. Crossplots and histogram plots for the correlations are presented in Figures 4-1 to 4-8. The crossplots show that all correlations are not predicting well when the bubblepoint pressure is above 4500psi. Histogram of errors plots and skewness show Standing and Vasquez and Beggs correlations error distribution closer to normal distribution with skewness of 0.17 and 0.13 respectively.

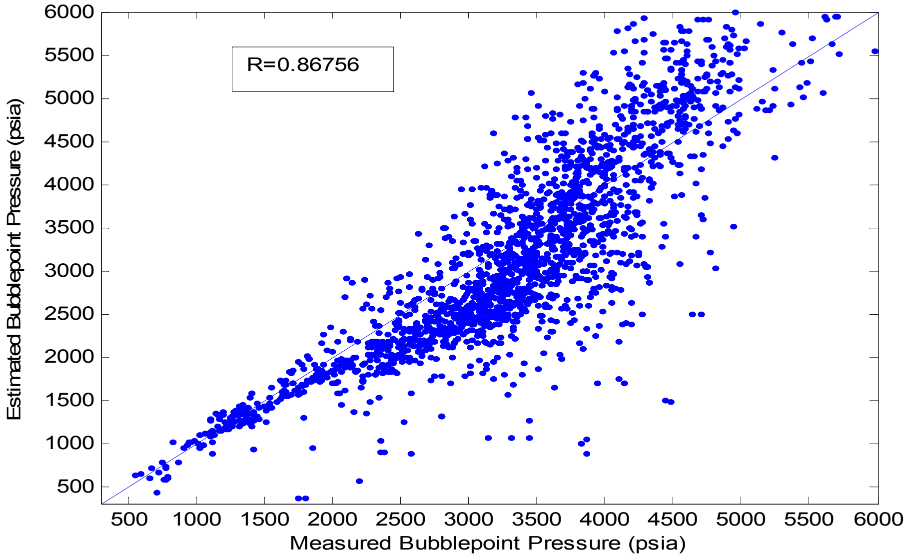

Figure 4-1 Crossplot for Pb (Standing Correlation)

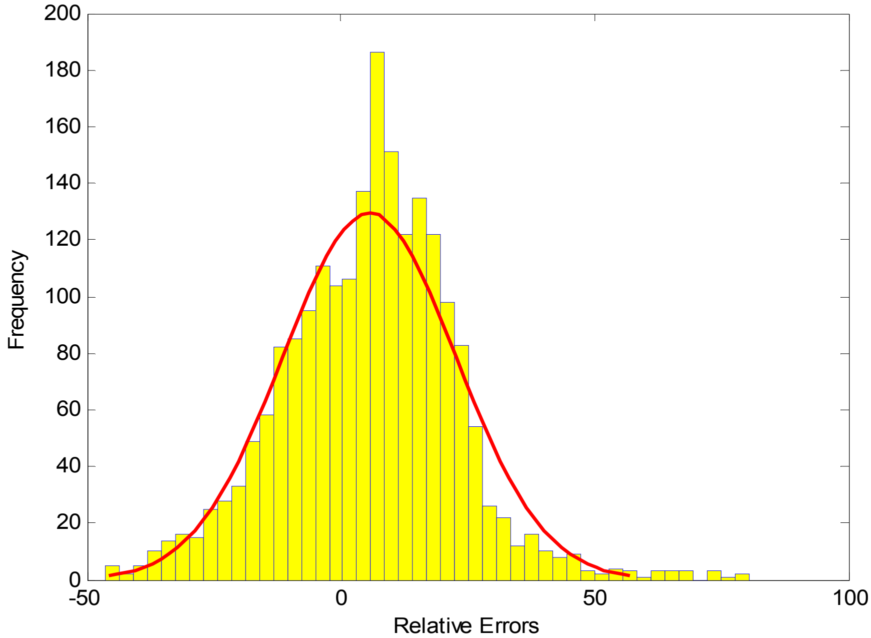

Figure 4-2 Histogram of Errors for Pb (Standing Correlation)

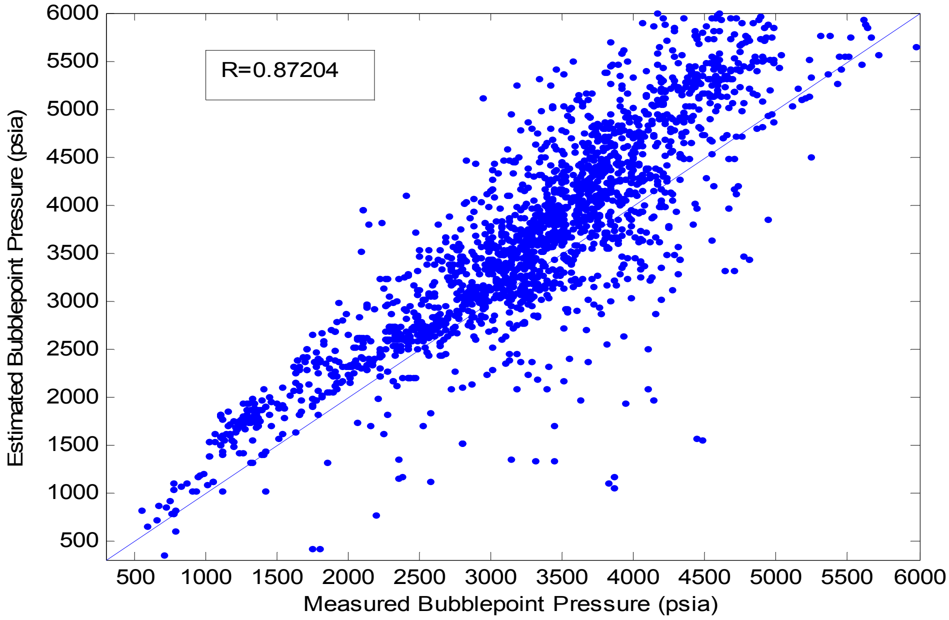

Figure 4-3 Crossplot for Pb (Glaso Correlation)

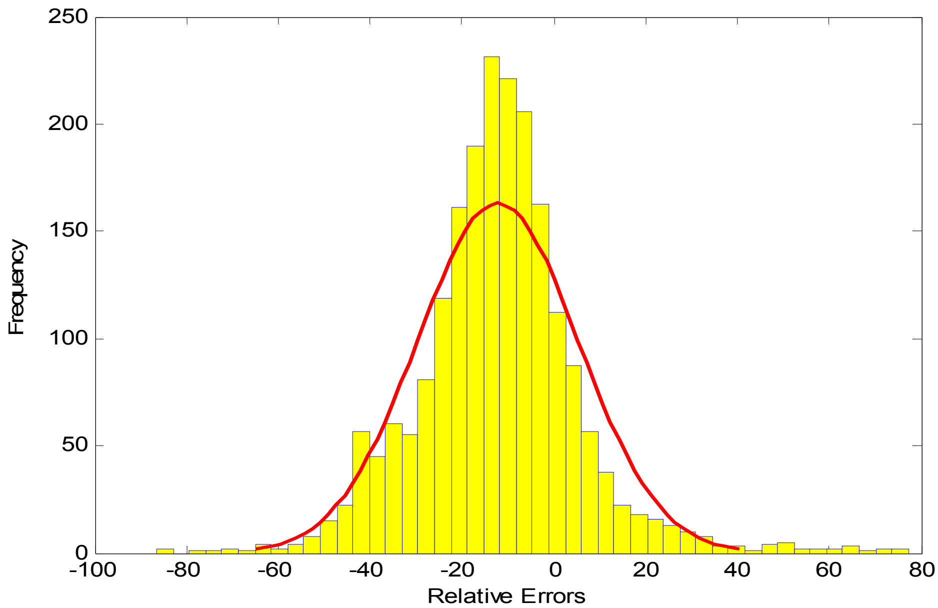

Figure 4-4 Histogram of Errors for Pb (Glaso Correlation)

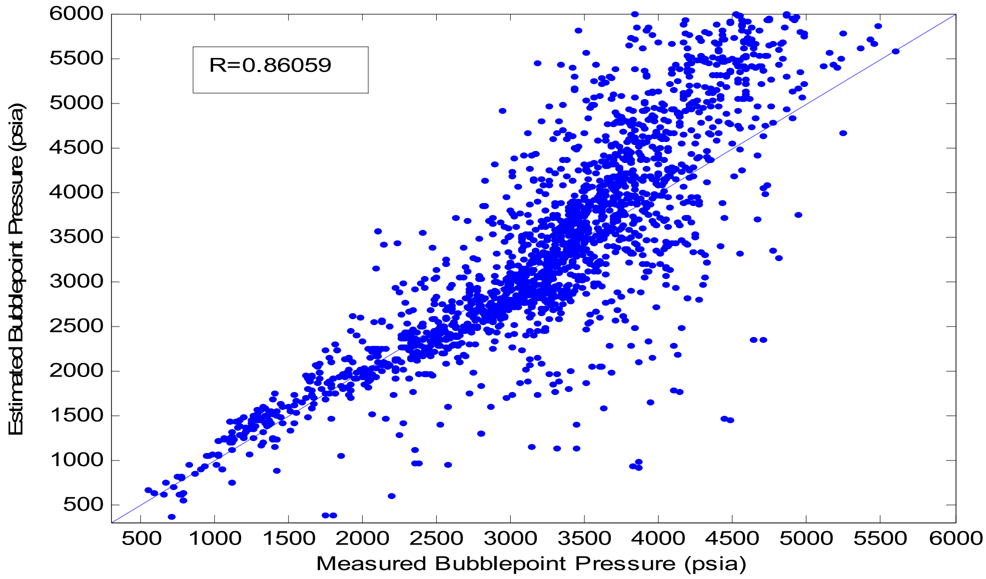

Figure 4-5 Crossplot for Pb (Vasquez and Beggs Correlation)

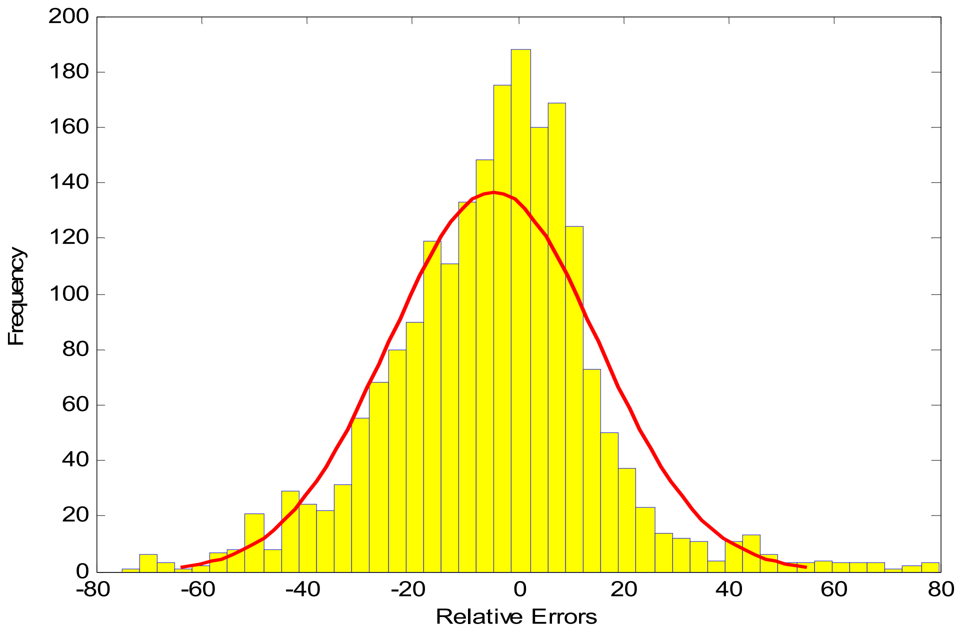

Figure 4-6 Histogram of Errors for Pb (Vasquez and Beggs Correlation)

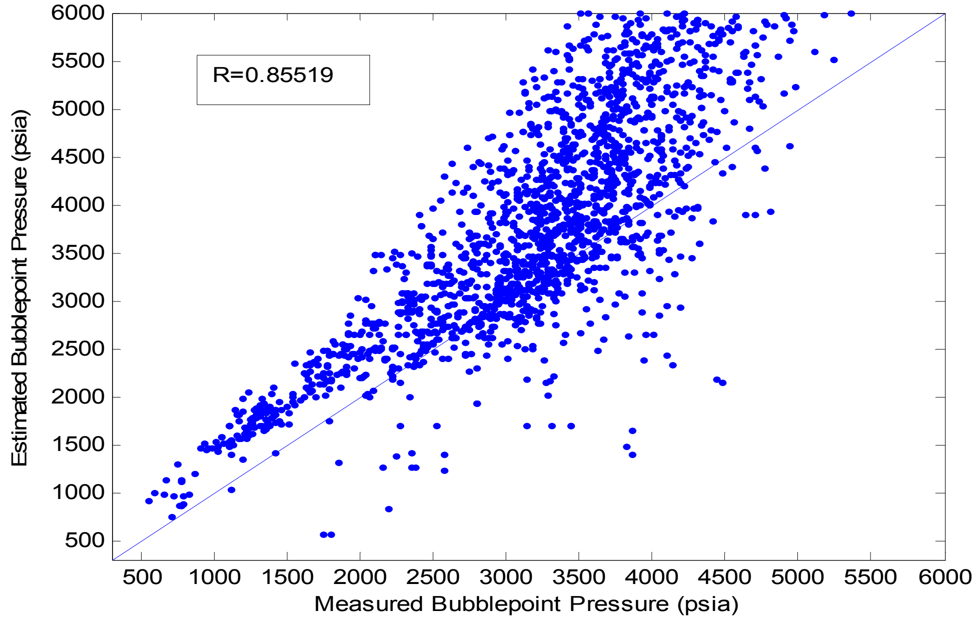

Figure 4-7 Crossplot for Pb (Al-Marhoun Correlation)

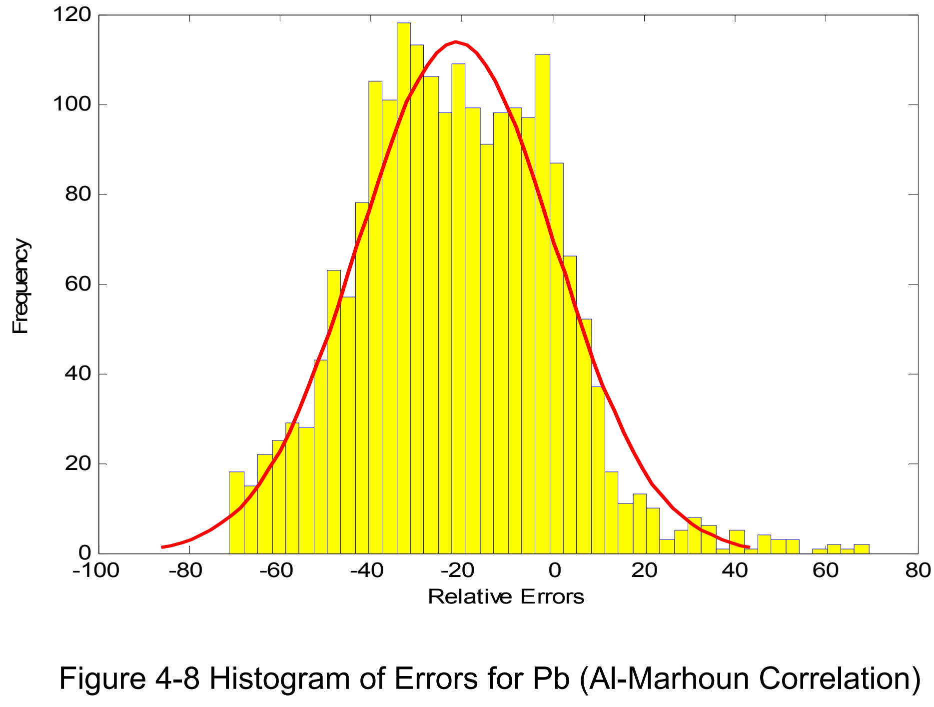

Figure 4-8 Histogram of Errors for Pb (Al-Marhoun Correlation)

4.2 Solution Gas-Oil Ratio

In 1987, Saleh et al [20] published their work on the evaluation of empirical correlations for Egyptian oils. They used the same data utilized for the evaluation of bubblepoint pressure correlations. They evaluated Standing, Vasquez and Beggs, Lasater and Glaso correlation for estimating solution GOR. They recommended the use of Glaso's GOR correlation (1980) for Egyptian crude with average absolute percent error of 46.48.

In 1990, Sutton and Farshad [21] published an evaluation of the four correlations studied by Ostermann using Gulf of Mexico crude oils. Standing (1947), Vasquez and Beggs (1980), Lasater (1958) and Glaso (1980) correlations were evaluated for solution GOR. The study shows that Glaso correlations for solution GOR provided the best result of all the correlations evaluated with average absolute error of 17.63.

In 2004, Al-Marhoun evaluated Standing, Vasquez and Beggs, and Al-Marhoun solution gas-oil ratio using the same data utilized for the evaluation of bubblepoint pressure correlations. Al-Marhoun (1988) correlation has the least average absolute relative error of 12.29.

In this study, Standing [3], Glaso [7] ,Al-Marhoun [8], and Vasquez and Beggs [5] correlations for solution gas-oil ratio are evaluated using Nigerian data. Statistical error analysis was used to evaluate the performance of the correlations. The statistical accuracy of solution as-oil ratio is shown in the Table 4-2. Graphical analysis show of crossplots and histograms of relative error are shown in figures 4.9-16.

As can be seen from Table 4-2 Vasquez and Beggs correlation performs better than Standing and Al-Marhoun correlations with average and absolute relative errors of 3.959 and 18.6 respectively. This performance is followed by Glaso (1980) with average and absolute relative errors of 9.788 and 19.32 respectively. Crossplots for the correlations as shown in Figures 4-9 to 4-16 indicates that Al-Marhoun correlation is not predicting well when the GOR is above 600scf/stb. Likewise, Standing (1947) correlation performance becomes bad at GOR above 1200scf/stb. This is shown in Figure 4-9. Histogram of errors plots, skewness and kurtosis values show that the the correlations error distribution are similar and are not normally distributed. All the correlations are skewed to the left. This is also indicated by negative values for skewness for all the correlations.

Table 4-2 Statistical Accuracy of Solution GOR

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Standing(1947)	-13.69	22.23	0.006	612.8	42.47	0.90	-6.68	75.79
Glaso(1980)	9.788	19.32	0.008	345.9	30.	0.926	-6.053	59.58
Vasquez and Beggs(1980)	3.959	18.6	0.0143	402.93	32.02	0.815	-5.6365	55.55
Al-Marhoun(1988)	20.74	28.16	0.000	405.3	36.69	0.87	-5.64	58.90

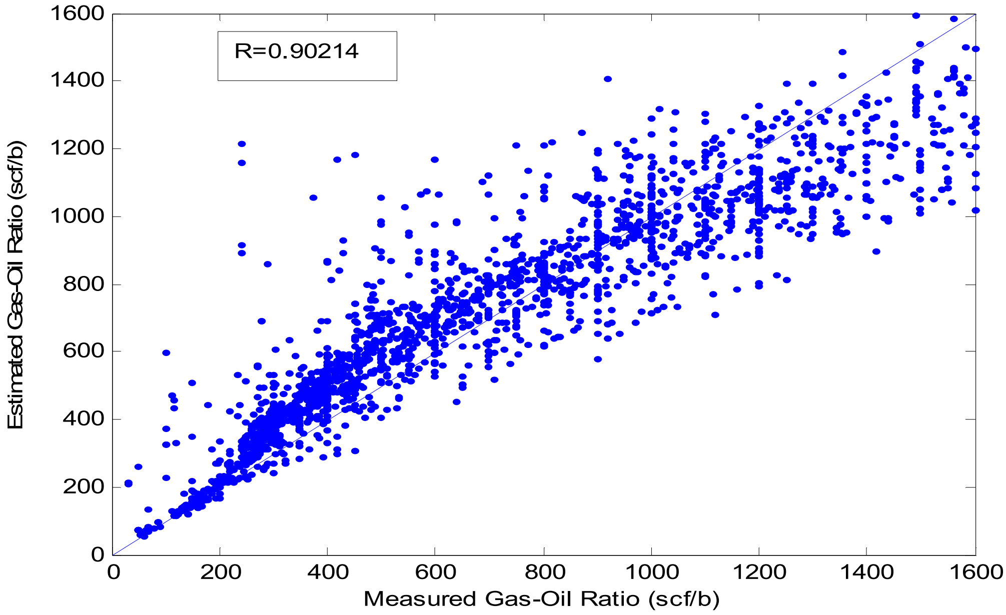

Figure 4-9 Crossplot for Solution GOR (Standing Correlation)

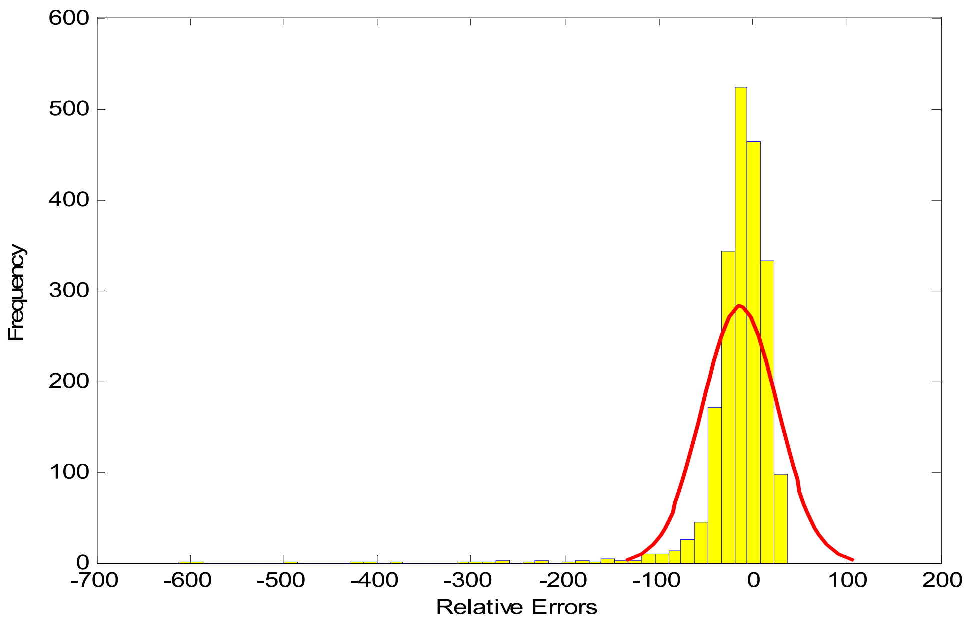

Figure 4-10 Histogram of Errors for Solution GOR (Standing Correlation)

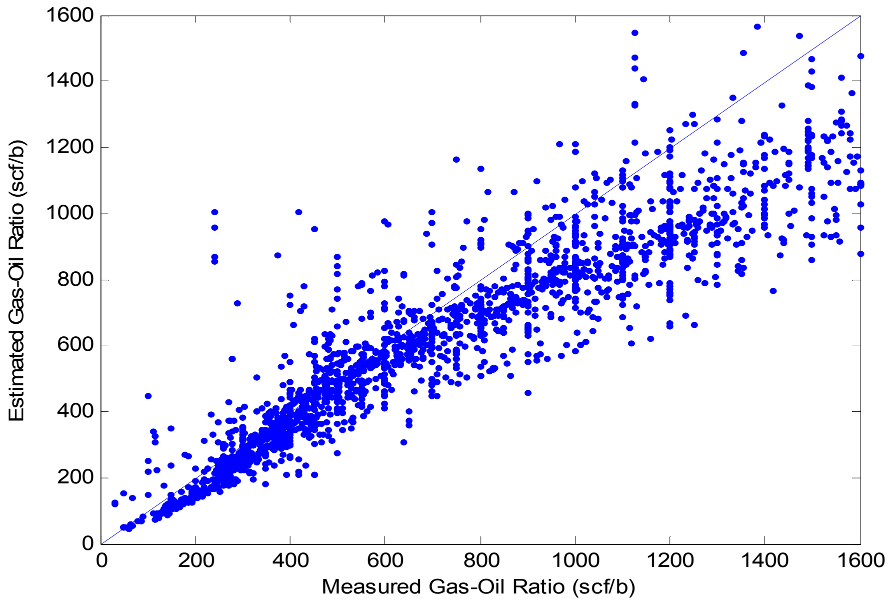

Figure 4-11 Histogram of Errors for Solution GOR (Glaso Correlation)

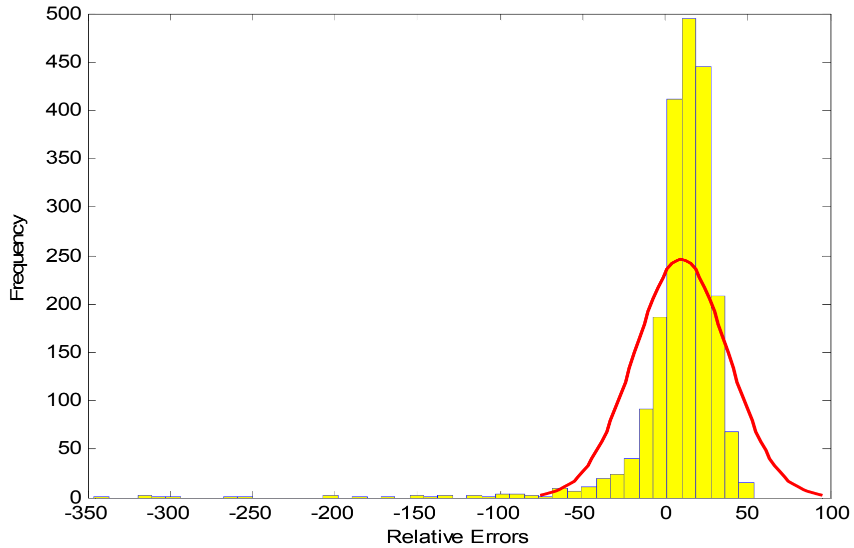

Figure 4-12 Histogram of Errors for Solution GOR (Glaso Correlation)

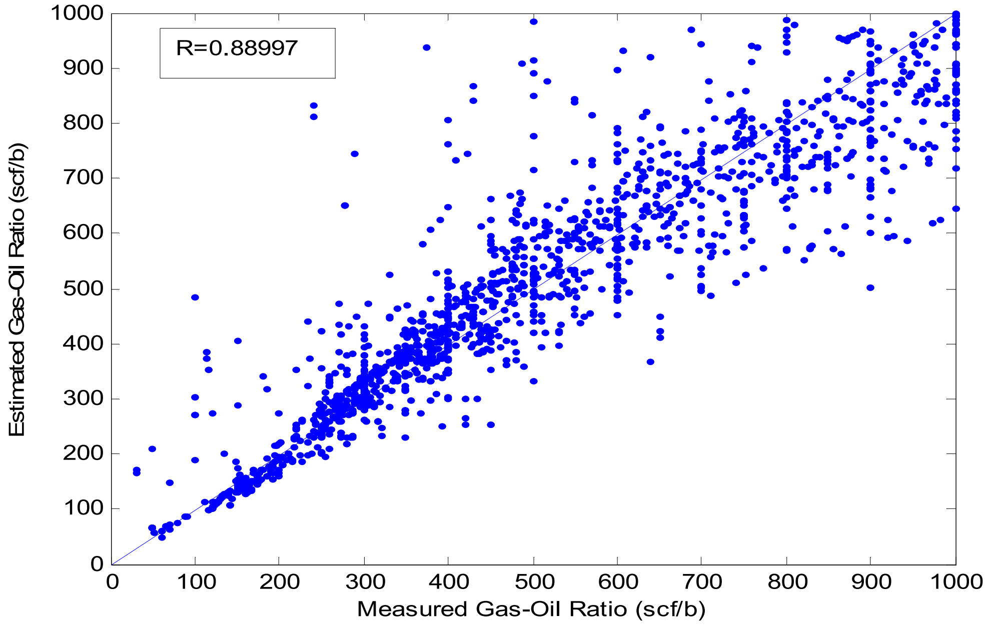

Figure 4-13 Crossplot for Solution GOR (Vasquez & Beggs Correlation)

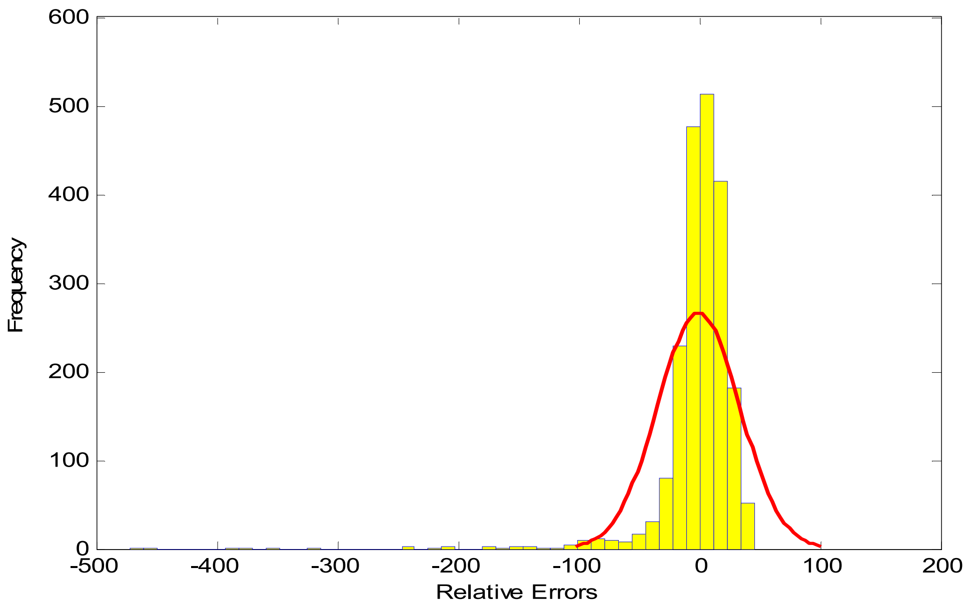

Figure 4-14 Histogram of Errors for Solution GOR (Vasquez & Beggs Correlation)

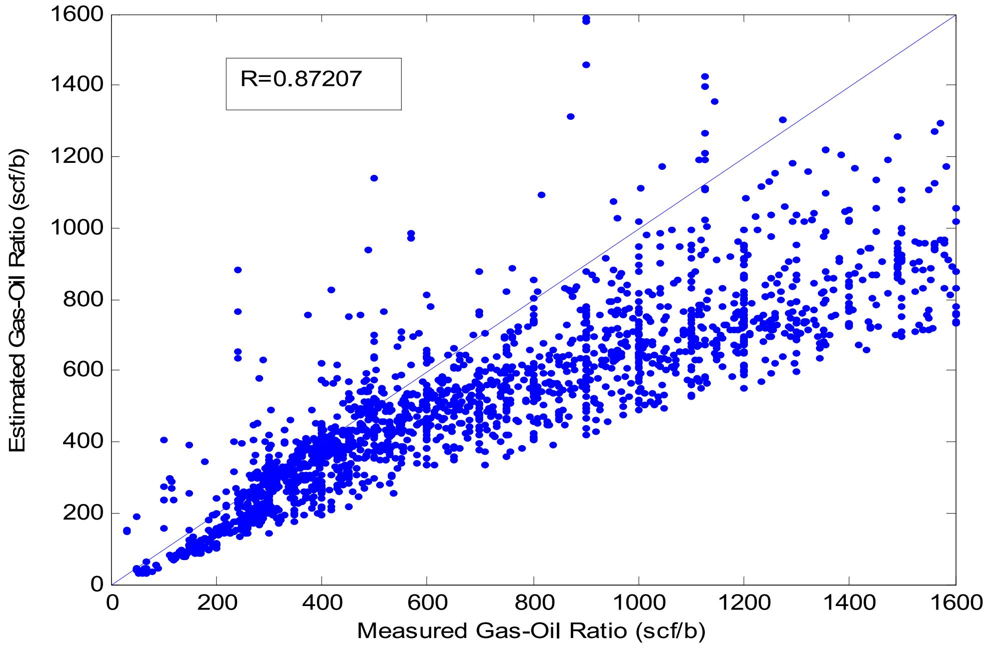

Figure 4-15 Crossplot for Solution GOR (Al-Marhoun Correlation)

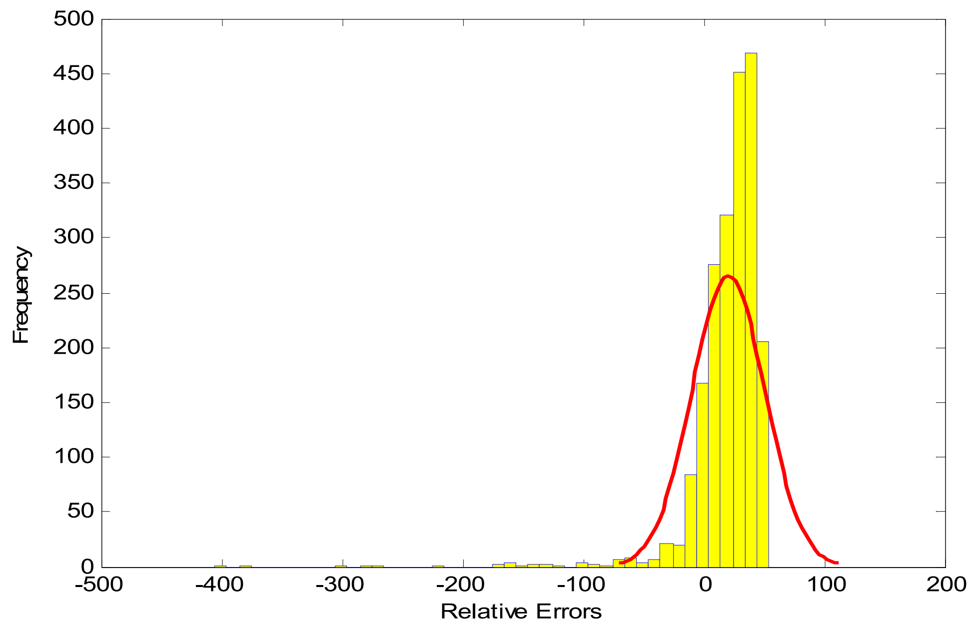

Figure 4-16 Histogram of Errors for Solution GOR (Al-Marhoun Correlation)

4.3 Oil Formation Volume Factor at Bubblepoint

In 1983, Ostermann et al [19] evaluated published Oil FVF at Bubblepoint correlations using Alaskan fluid data. PVT reports for 4 fields in the Cook Inlet Basin were used. 8 data points were used in the evaluation. They evaluated Standing [3], Vasquez and Beggs [5], and Glaso [7] correlations. The result of their evaluation shows that Standing correlation performs best for oil formation volume factor at bubblepoint using Alaskan crudes with a mean error of -0.75% and standard deviation of 0.69%.

Furthermore, in 1987, Saleh et al [20] published their work on the evaluation of oil FVF at bubblepoint empirical correlations for Egyptian oils. They evaluated Glaso [7], Standing [3], and Vasquez and Beggs [5] correlations. They recommend the use of Standing's FVF [3] correlation for Egyptian crude with average absolute percent error of 5.55 and standard deviation of 6.67.

In 1990, Sutton and Farshad [21] published an evaluation of the four correlation studied by Ostermann [19] using Gulf of Mexico crude oils. They used the same data employed for bubblepoint pressure correlations. The study shows that Glaso correlations for oil formation volume factor at bubblepoint perform proved to be the best of all the correlation evaluated with average absolute error of 2.38.

In 1996, Mahmood and Al-Marhoun [22] published their study on evaluation of oil FVF correlations for Pakistani crude oils using the same data utilized for bubblepoint pressure correlations. Al-Marhoun (1992) oil formation volume factor at bubblepoint correlation gave the best results with an average absolute error of 1.23%.

In 1999, Al-Shammasi [23] published a study on the evaluation of Standing [3], Al-Marhoun (1988), Vasquez and Beggs, Glaso, Kartoatmodjo and Schmidt, Dokla and Osman, Majeed and Salman, Almehaideb, Laster, Macary and El Batanoeney, Petrosky and Farshad, Al-Marhoun (1992) and Omar and Todd correlations for oil FVF at bubblepoint using a total of 1345 data sets from 13 different published literature papers and Kuwait reservoirs. His study shows that Petrosky and Farshad correlation outperforms other correlations with the average absolute relative error of 1.73.

In 2004, Al-Marhoun (1992) evaluated Standing (1946), Vasquez and Beggs (1980), and Al-Marhoun (1992) oil FVF at bubblepoit pressure using the same data used for bubblepoint pressure correlations evaluation. Al-Marhoun (1992) correlation has the least average absolute relative error of 0.72.

In this study, Standing [3], Glaso [7] , Al-Marhoun [12], Vasquez and Beggs [5] and Petrosky and Farshad [10] correlations for oil FVF at bubblepoint were evaluated using Nigerian data. Statistical error analysis was used to evaluate the performance of the correlations. The statistical accuracy, crossplots and histograms of errors of solution gas-oil ratio are shown in the Table 4-3 and Figure 4-17-4-26 respectively.

In Table 4-3 Al-Marhoun (1992) shows the most outstanding performance with average and absolute relative errors of 0.59, and 3.28 respectively. It also has highest correlation coefficient of 0.95. Its error distribution also shows normal behavior and the distribution peaked at the center with highest kurtosis of 9.6522. This performance is closely followed by Standing, and Petrosky and Farshad, then Glaso with Vasquez and Beggs performance being the poorest of all. Figures 4-17, 4-19, 4-21, 4-23, and 4-25 show crossplots for Standing, Glaso, Vasquez and Beggs, Al-Marhoun, and Petrosky and Farshad correlations respectively show that all correlations underpredict the oil FVF at bubblepoint above 1.8. Figures 4-18, 4-20, 4-22, 4-24, and 4-26 show histogram plots of errors for Standing, Glaso, Vasquez and Beggs, Al-Marhoun, and Petrosky and Farshad correlations respectively. Standing histogram of error distribution is most normally distributed with least skewness of 0.81.

Table 4-3 Statistical Accuracy of Oil FVF at Bubblepoint

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Standing(1947)	0.06	3.48	0.001	42.72	5.05	0.94	0.81	9.34
Glaso(1980)	2.0149	3.73	0.003	43.7	5.44	0.94	0.77	9.02
Vasquez and Beggs(1980)	2.459	4.382	0.00408	43.362	6.23	0.927	0.89	6.14
Al-Marhoun(1992)	0.59	3.28	0.000	42.39	4.73	0.95	1.10	9.65
Petrosky & Farashad(1993)	1.61	3.46	0.0001	42.7	5.12	0.95	0.98	8.61

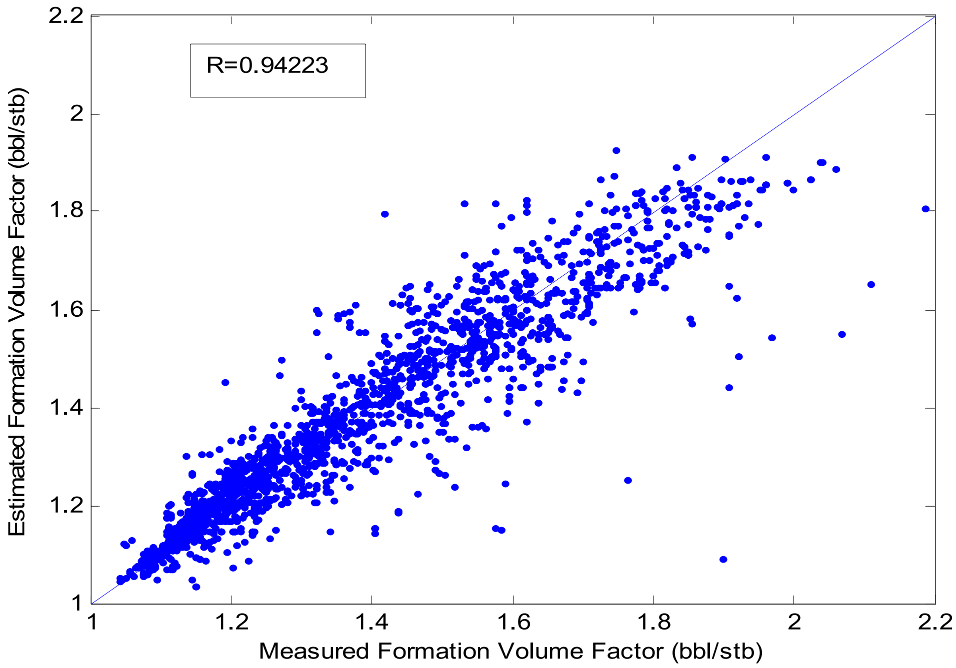

Figure 4-17 Crossplot for Oil FVF at Pb (Standing Correlation)

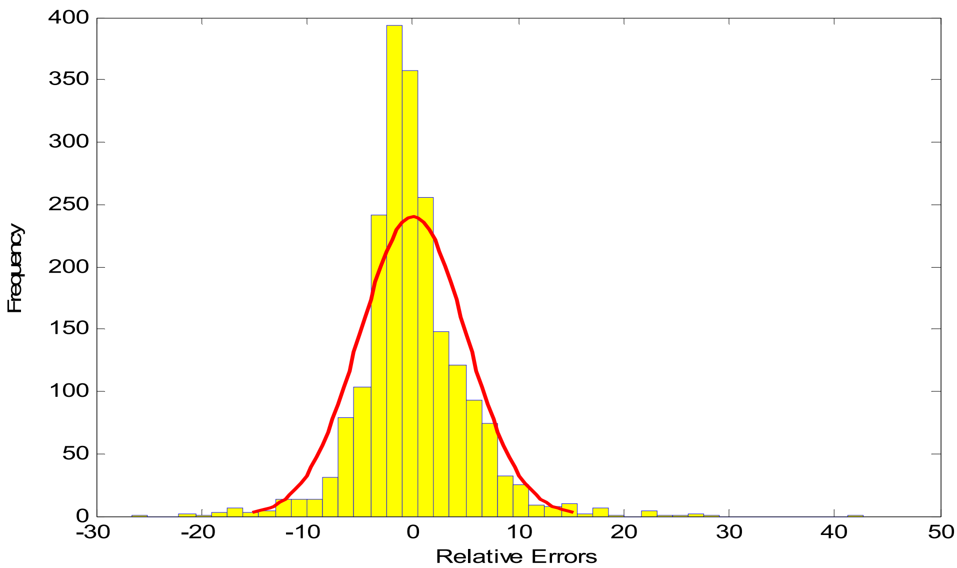

Figure 4-18 Histogram of Errors for Oil FVF at Pb (Standing Correlation)

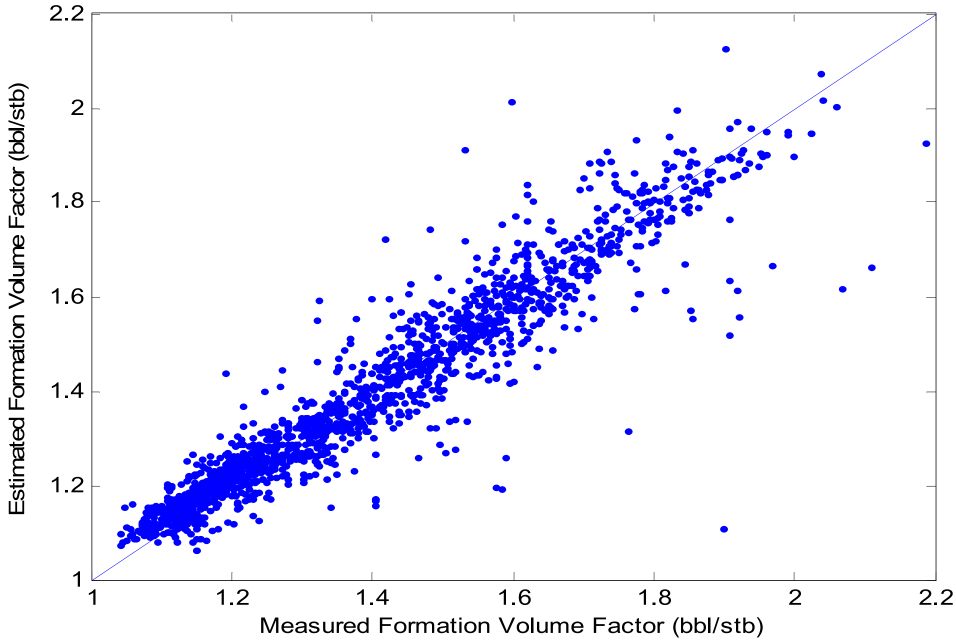

Figure 4-19 Crossplot for Oil FVF at Pb (Glaso Correlation)

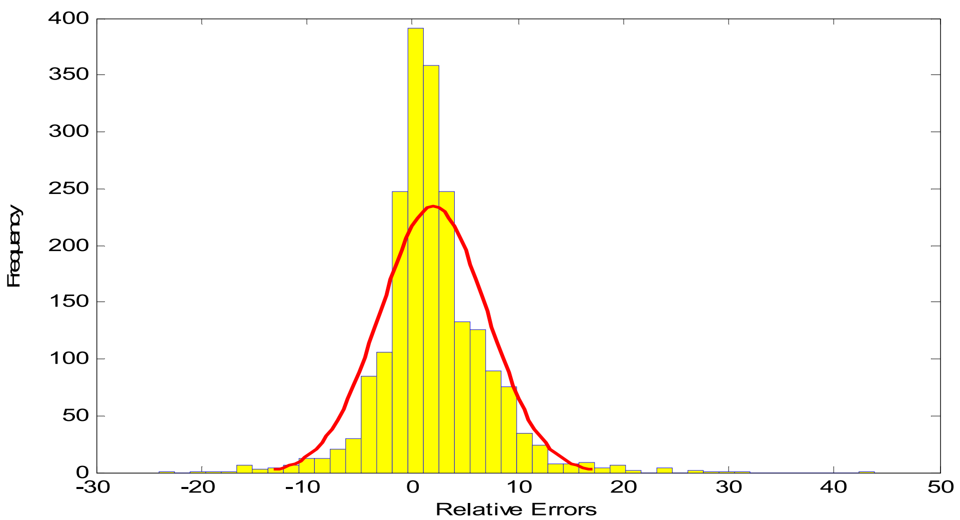

Figure 4-20 Histogram of Errors for Oil FVF at Pb (Glaso Correlation)

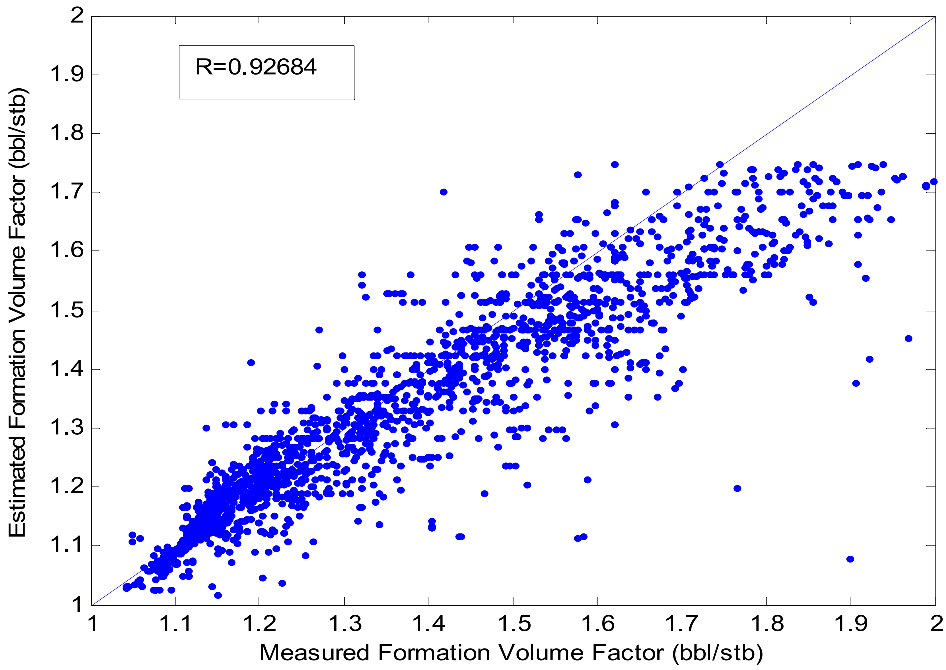

Figure 4-21 Crossplot for Oil FVF at Pb (Vasquez & Beggs Correlation)

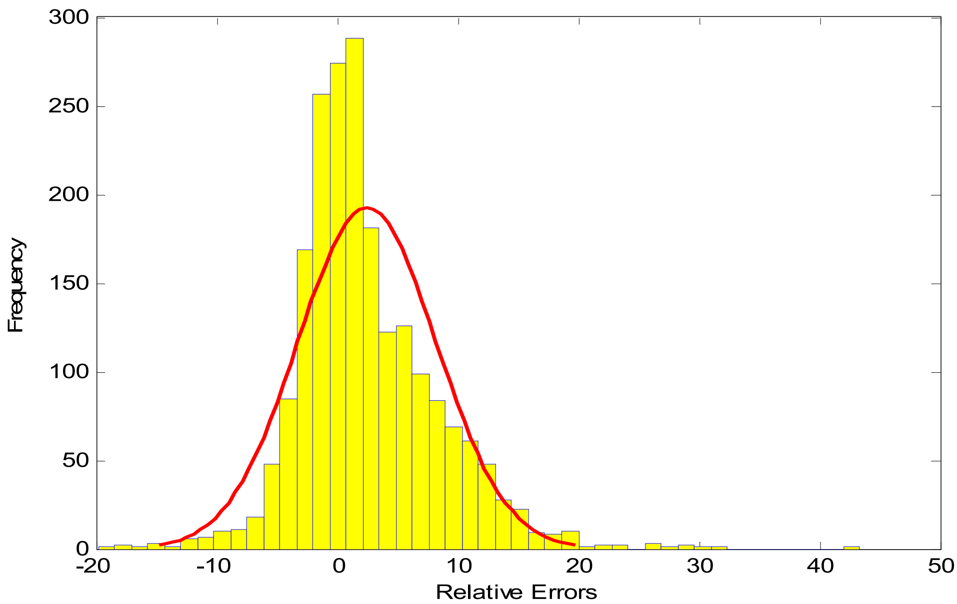

Figure 4-22 Histogram of Errors for Oil FVF at Pb (Vasquez & Beggs Correlation)

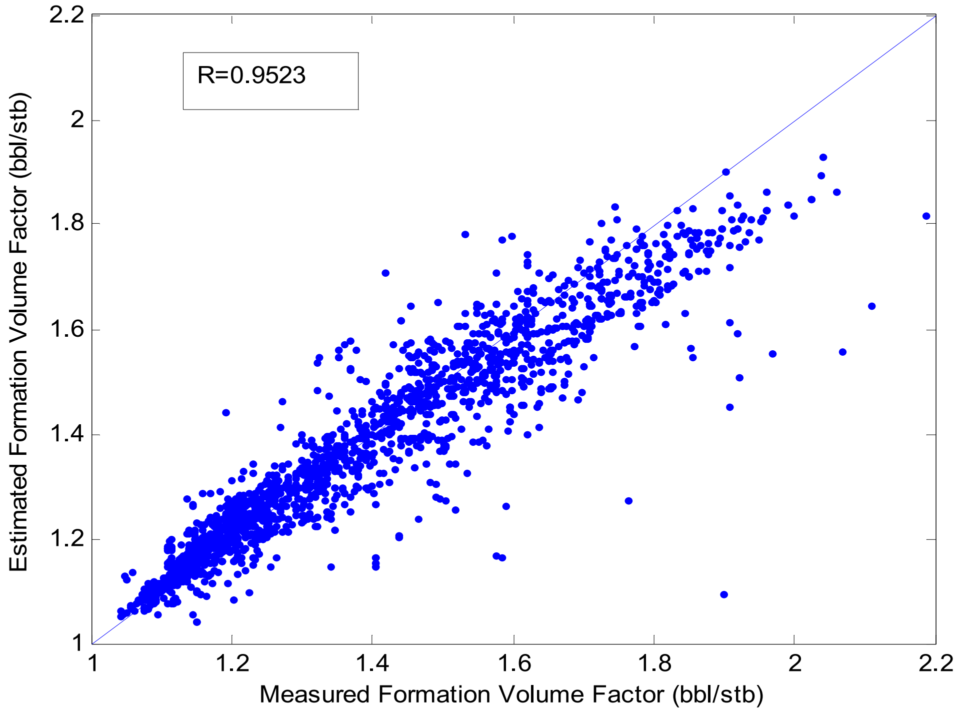

Figure 4-23 Crossplot for Oil FVF at Pb (Al-Marhoun Correlation)

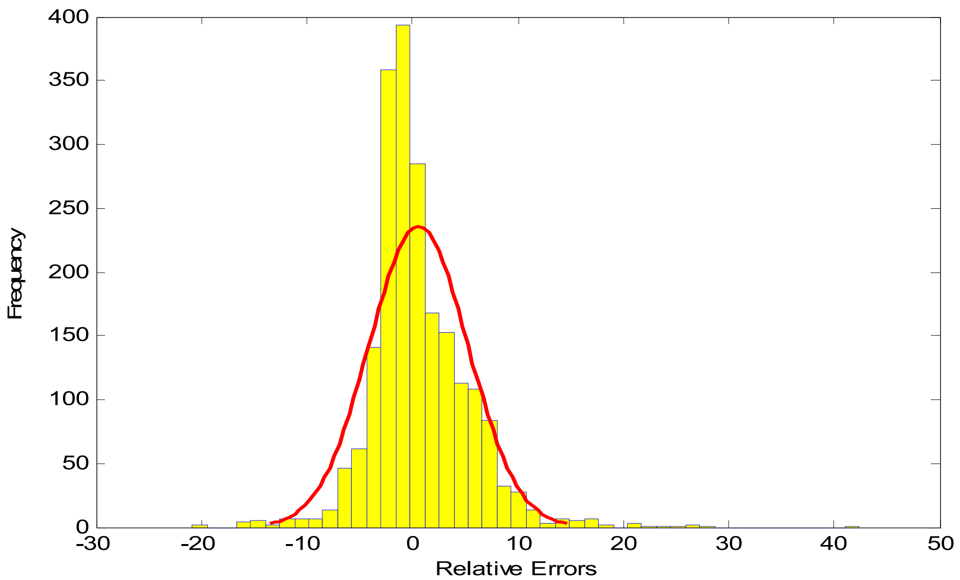

Figure 4-24 Histogram of Errors for Oil FVF at Pb (Al-Marhoun Correlation)

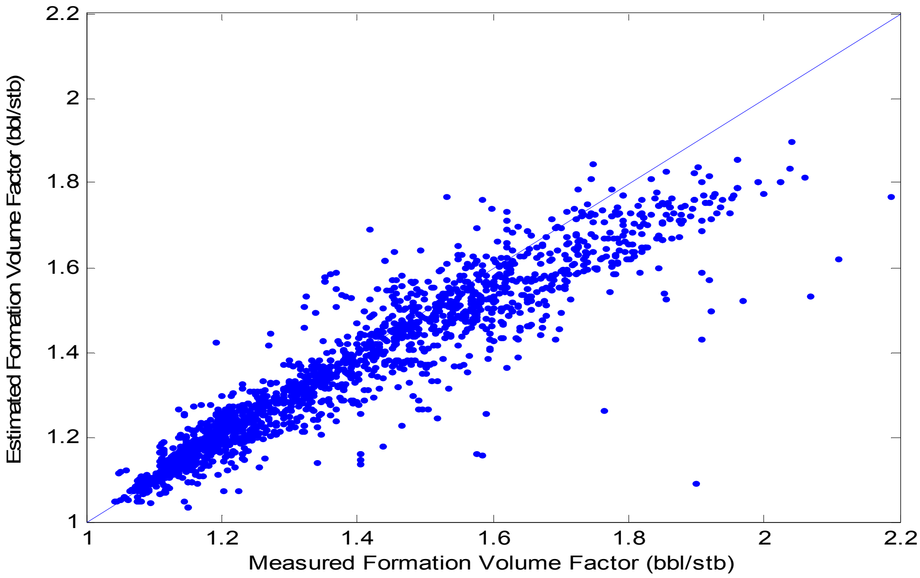

Figure 4-25 Crossplot for Oil FVF at Pb (Petrosky & Farshad Correlation)

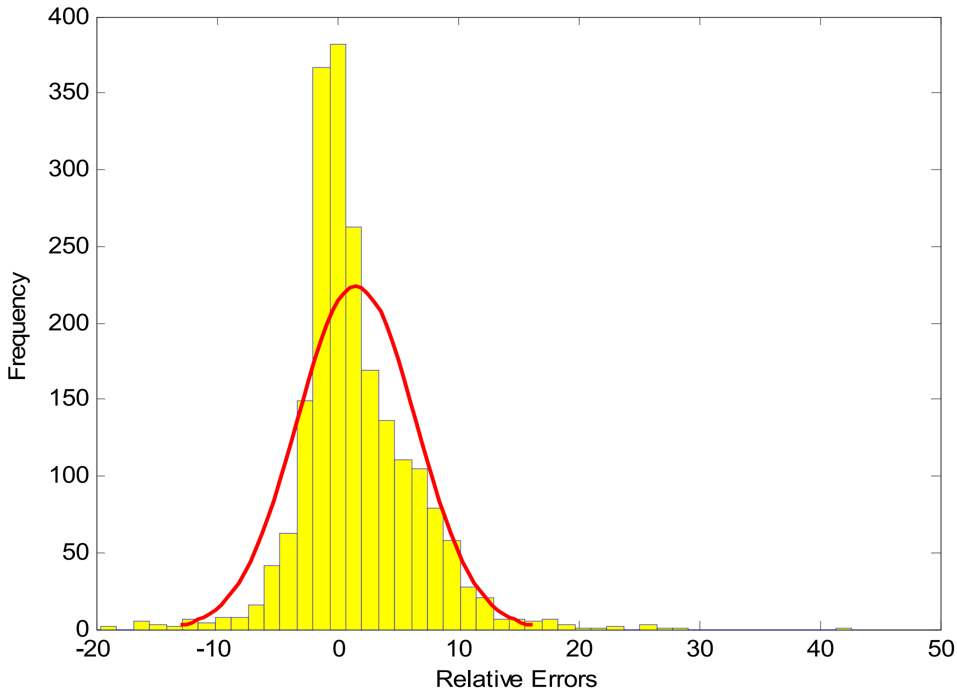

Figure 4-26 Histogram of Errors for Oil FVF at Pb (Petrosky & Farashad Correlation)

4.4 Oil Viscosity at Bubblepoint

In 1983, Ostermann et al [19] evaluated Beggs and Robinson [14] correlation for oil viscosity at bubblepoint using Alaskan fluid data. Mean error of -0.56 and standard deviation of 12.00 were recorded.

Furthermore, in 1987, Saleh et al [20] published their work on the evaluation of empirical correlations for Egyptian oils. They evaluated Chew and Connally [13] and Beggs and Robinson [14] correlations for oil viscosity at bubblepoint. The results of the evaluation show that Chew and Connally' correlation provided slightly better results than the Beggs end Robinson' correlation with average absolute percent relative error of 23.02.

In 1990, Sutton and Farshad [21] published evaluation of chew and Connally [13], and Beggs and Robinson [14] correlation for oil viscosity at bubblepoint using Gulf of Mexico crude oils. They used 285 data points for gas saturated oil and 134 data points for under-saturated oil representing 31 different crude oils and natural gas systems. Beggs and Robinson correlation was found to be more accurate with average absolute relative error of 17.31.

In 1996, Mahmood and Al-Marhoun [22] published their study on evaluation of oil viscosity at bubblepoint correlations for Pakistani crude oils. They used 166 data sets from 22 different crude samples for the evaluation. Chew and Connally correlation was found to be the best with the least error of 12.21.

In 2004, Al-Marhoun [24] evaluated Beggs and Robinson [14], Chew and Connally [13], and Labedi [17] correlations for oil viscosity at bubblepoint using 296 data points from obtained from Middle East crude oils. Beggs and Robinson correlation was found to have the least average absolute relative error of 16.50.

In this study, Beggs and Robinson [14], Chew and Connally [13], Labedi [17], and Khan et al [15] correlations for the oil viscosity at bubblepoint were evaluated using Nigerian data. Statistical error analysis was used to evaluate the performance of the correlations.

Table 4-4 Statistical Accuracy of Oil viscosity at Pb

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Chew & Connally(1959)	-71	75	0.019	538.3	92.7	0.95	-1.70	11.33
Beggs & Robinson(1975)	-23	31	0.025	285.7	41.6	0.92	-1.38	12.36
Labedi(1992)	-109	116	0.045	1042	149.1	0.96	-1.23	7.83
Khan et al(1991)	-45	58	0.014	5026	146.7	0.92	-23.26	804.57

The statistical accuracy of oil viscosity at bubblepoint is shown in Table 4-4 and crossplots and histograms of relative error are as shown in Figure 4-27-4-34.

The results shown in Table 4-4 indicate that Beggs and Robinson correlation predicts better inspite high value compared to other three correlations with average relative and absolute errors, and RMS of -23.04, 31.15 and 41.62 respectively. This performance is followed by Khan et al correlation with absolute relative error of 57.57. The crossplots and histogram of error plots are as shown in Figures 4-27 to 4-34. Except for Beggs and Robinson correlation, crossplots for all correlations show that all correlations are not predicting well at higher viscosity; skewed to the left and therefore, the errors are not normally distributed. This is also evident from negative values for skewness shown in Table 4-4.

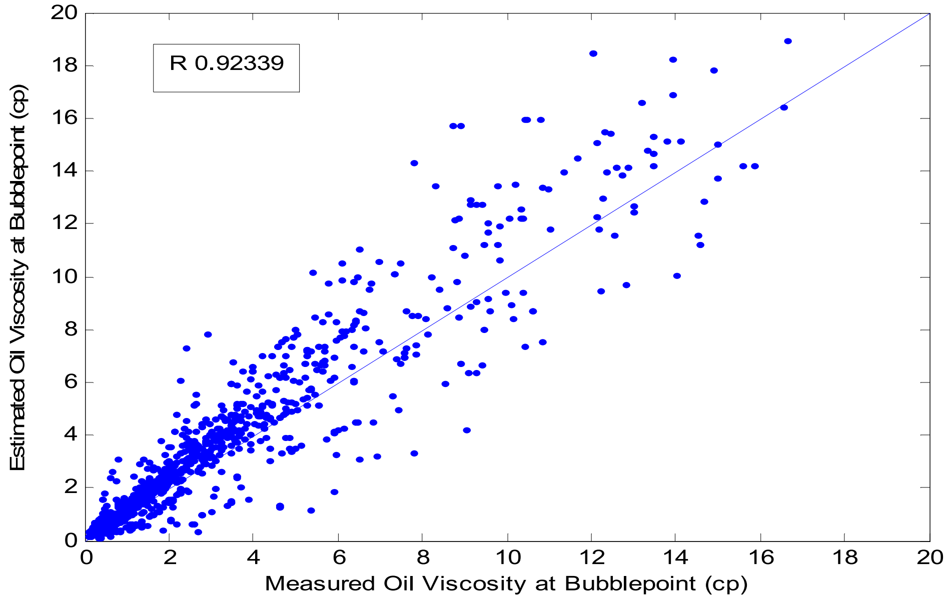

Figure 4-27 Crossplot for Oil Viscosity at Pb (Beggs and Robinson Correlation)

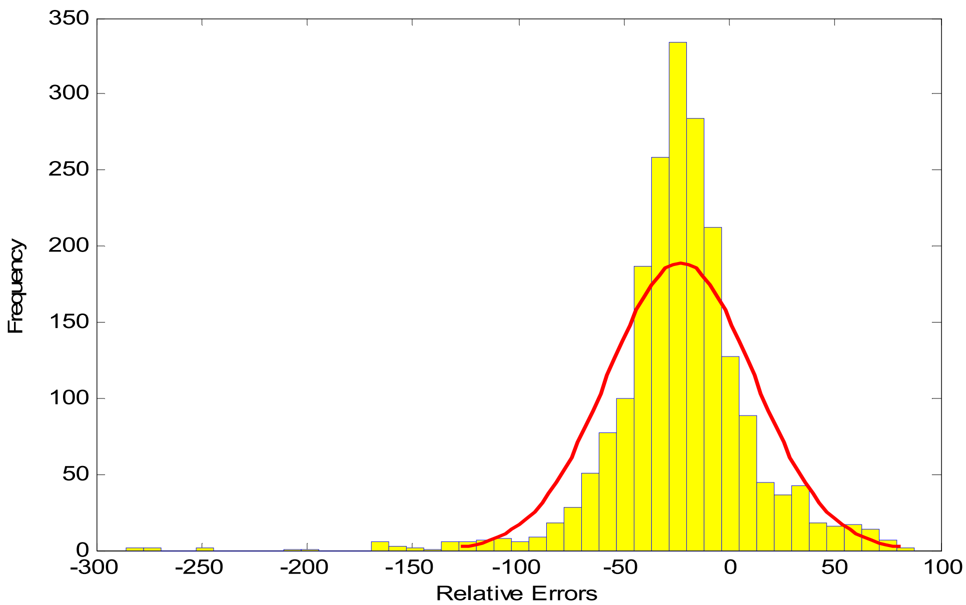

Figure 4-28 Histogram of Errors for Oil Viscosity at Pb (Beggs and Robinson Correlation)

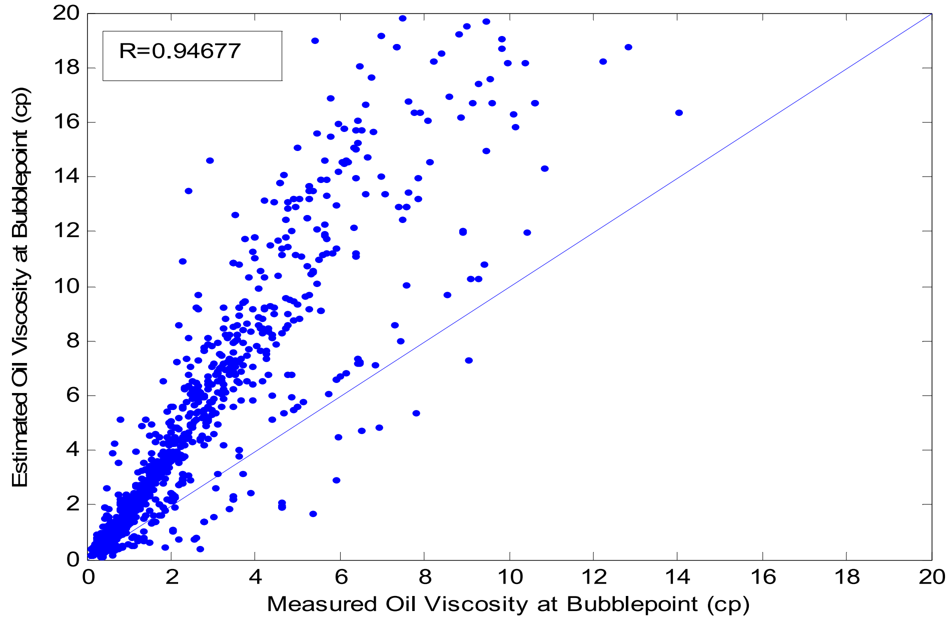

Figure 4-29 Crossplot for Oil Viscosity at Pb (Chew and Connally Correlation)

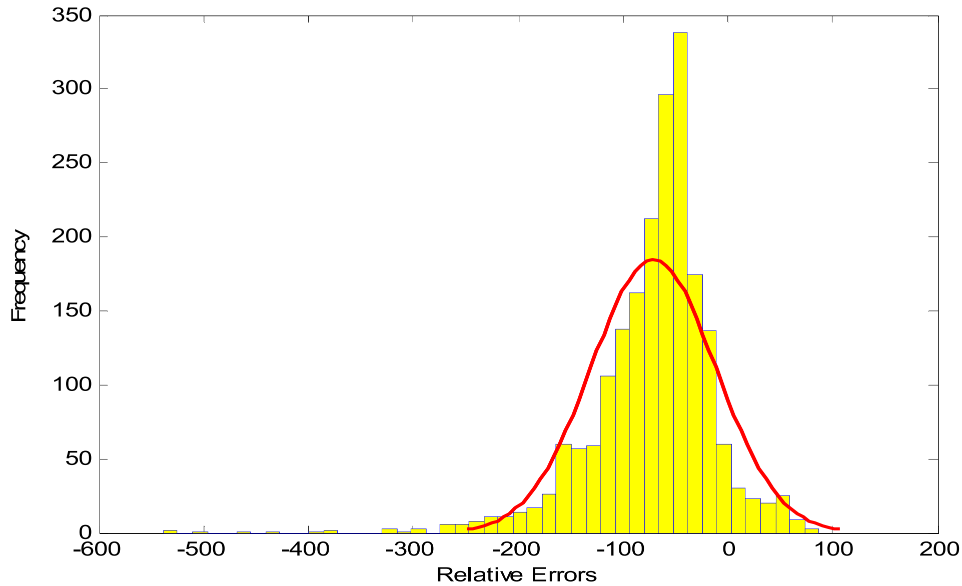

Figure 4-30 Histogram of Errors for Oil Viscosity at Pb (Chew and Connally Correlation)

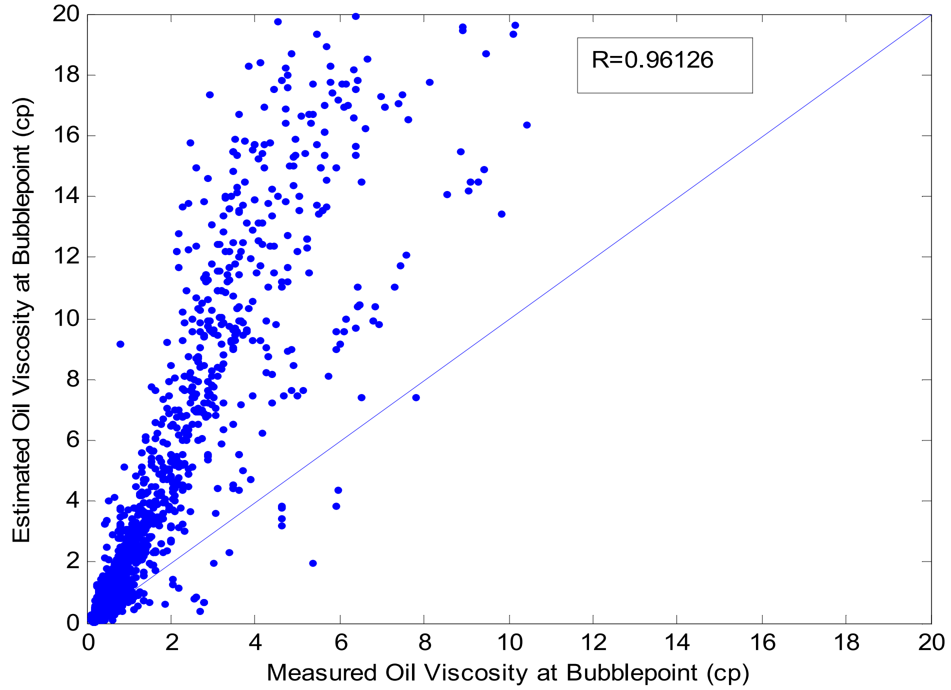

Figure 4-31 Crossplot for Oil Viscosity at Pb (Labedi Correlation)

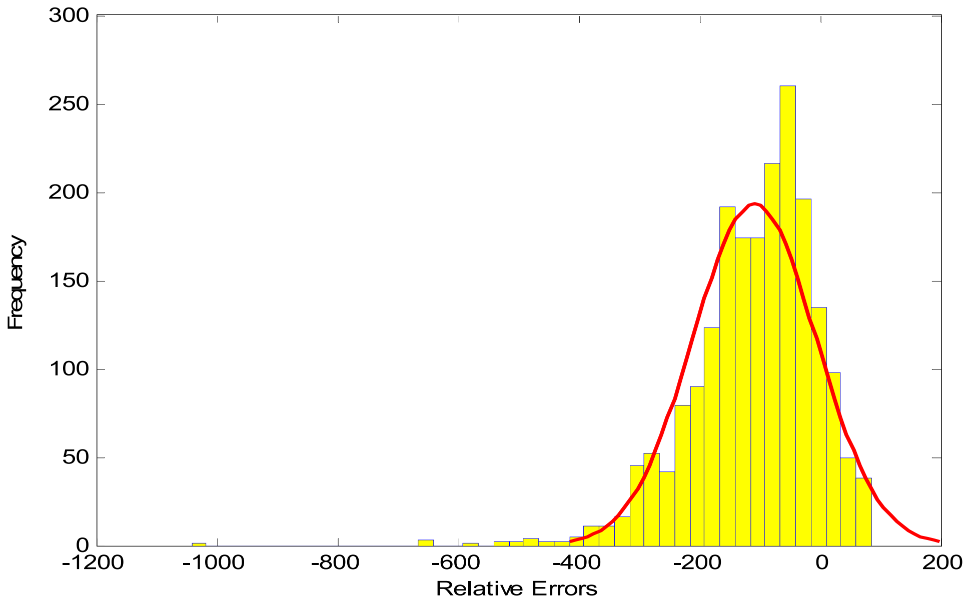

Figure 4-32 Histogram of Errors for Oil Viscosity at Pb (Labedi Correlation)

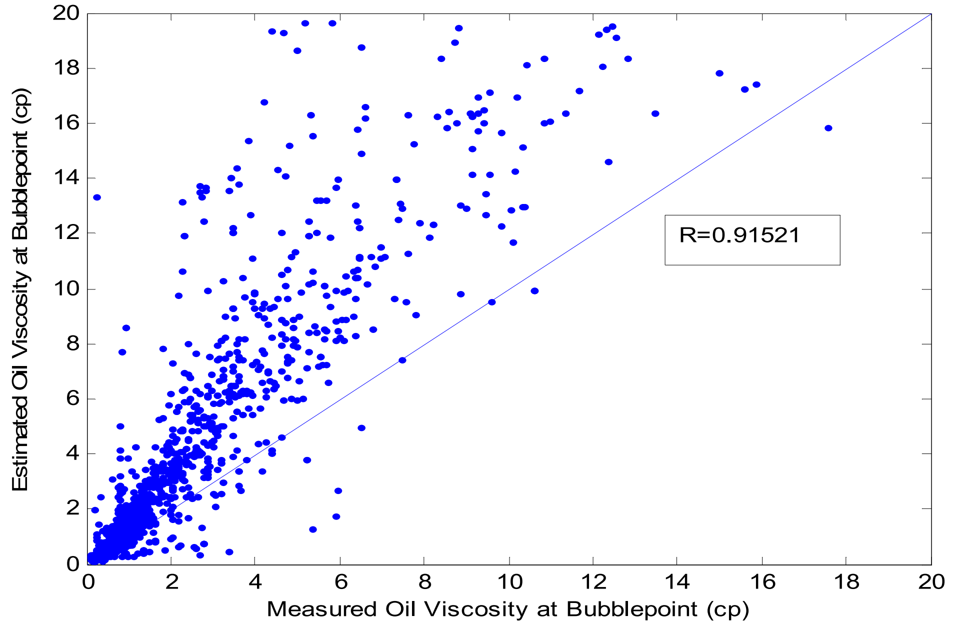

Figure 4-33 Crossplot for Oil Viscosity at Pb (Khan et al Correlation)

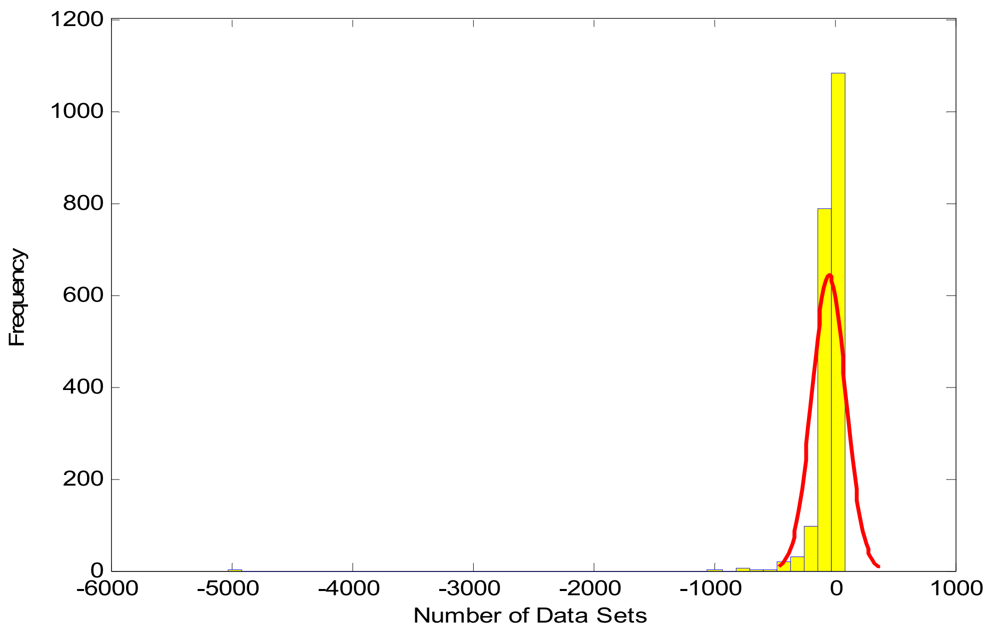

Figure 4-34 Histogram of Errors for Oil Viscosity at Pb (Khan et al Correlation)

4.5 Dead-Oil Viscosity

In 1983, Ostermann et al [19] evaluated Beggs and Robinson[14] correlation for the dead oil viscosity correlations using Alaskan fluid data. Mean relative error of 13.26 and standard deviation of 10.50 were reported.

In 1990, Sutton and Farshad [21] published evaluation of Beal [18], Beggs and Robinson [14] and Glaso [7] correlations for the dead oil viscosity using Gulf of Mexico crude oils. They used 285 data points for gas saturated oil and 134 data points for under-saturated oil representing 31 different crude oils and natural gas systems. Glaso's correlation showed the best accuracy of the three correlations examined with average absolute relative error of 25.36.

In 1996, Mahmood and Al-Marhoun [22] published their study on evaluation of dead oil viscosity correlations for Pakistani crude oils. They used 166 data sets from 22 different crude samples for the evaluation. Beal, Beggs and Robinson, Glaso, Ng and Egbogah and Labedi correlations were evaluated. The Glaso (1980) was found to be relatively better for gravity higher than 34 °API. All of the correlations give high errors for low oil API gravity. They also reported that, except Beal (1946), all of the correlations overestimated dead oil viscosity values.

In 2004, Al-Marhoun [24] evaluated Beggs and Robinson [14], Glaso [7], and Labedi dead-oil viscosity correlations using 296 data points from obtained from Middle East crude oils. Glaso correlation is found to be better for higher API gravity. It has the least average absolute relative error of 24.75.

In this study, Beal [18], Beggs and Robinson [14], Glaso [7], and Labedi [17] correlations for the dead-oil viscosity were evaluated using Nigerian data. The statistical accuracy of dead-oil viscosity is shown in the Table 4-5 and crossplots and histograms of relative error are shown in Figure 4-35-4-42.

Table 4-5 Statistical Accuracy of Dead-Oil Viscosity

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Beal(1946)	13.64	46.88	0.050	922	75.99	0.88	-5.02	41.11
Beggs & Robinson(1975)	13.84	42.08	0.109	448	63.27	0.85	-3.72	21.17
Glaso(1980)	18.11	44.96	0.083	7672	68.58	0.89	-4.93	38.13
Labedi(1992)	-29.69	53.88	0.025	1323	112.78	0.89	-5.20	43.17

As indicated in the Table 4-5, the performance of Beggs and Robinson correlation is relatively better with average relative and absolute errors of 13.84 and 42.07 respectively. This is closely followed by Glaso with average absolute relative error of 44.96. However, crossplots Figure 4-37 shows that Beggs and Robinson correlation does not predict well at higher viscosities compared to other correlations. All the correlations are skewed to the left and are not normally distributed. This is indicated by negative value for skewness as shown in the histogram plots of Figures 4-36, 4-38, 4-40 and 4-42.

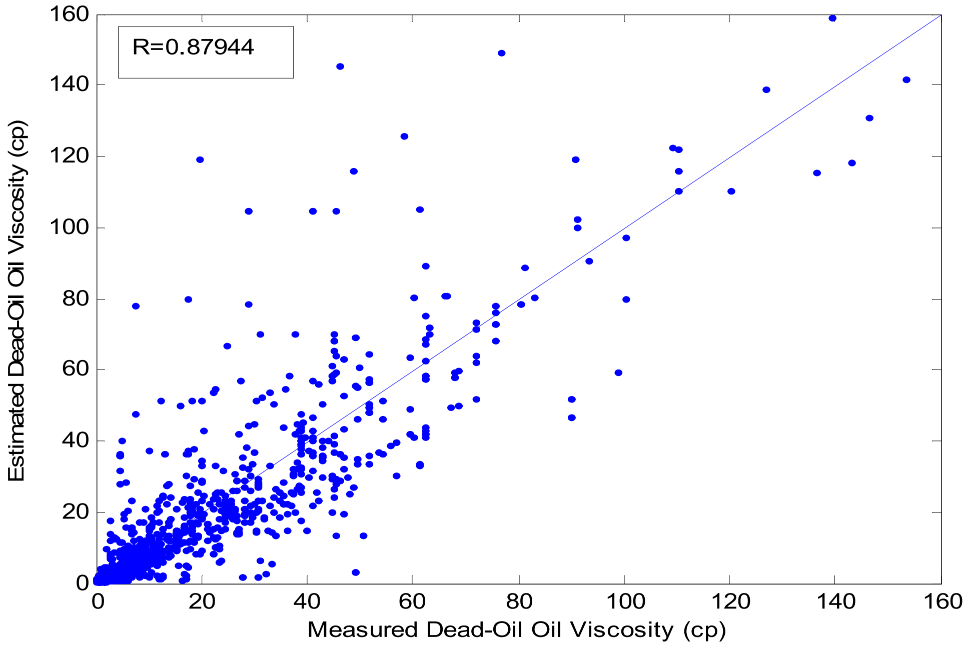

Figure 4-35 Crossplot for Dead-Oil Viscosity (Beal Correlation)

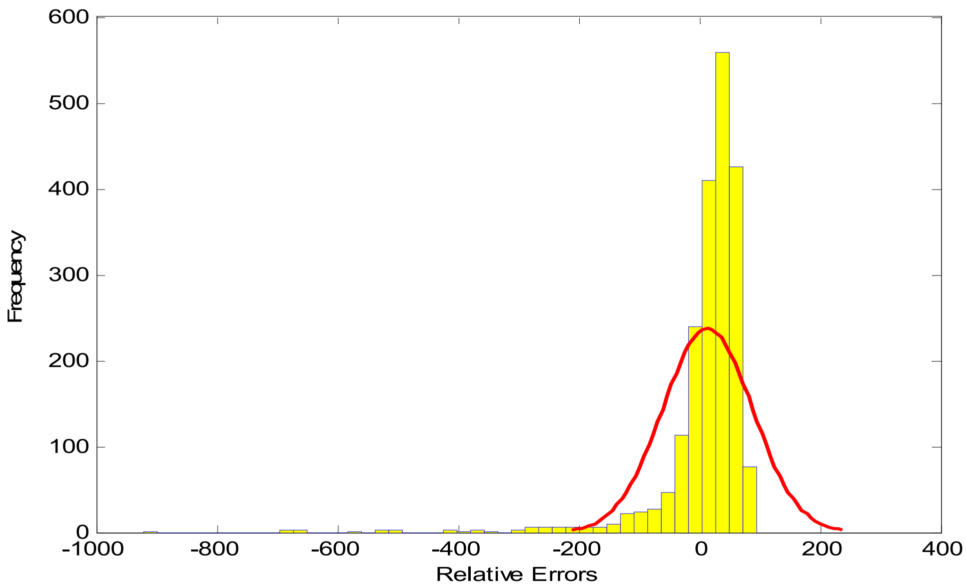

Figure 4-36 Histogram of Errors for Dead-Oil Viscosity (Beal Correlation)

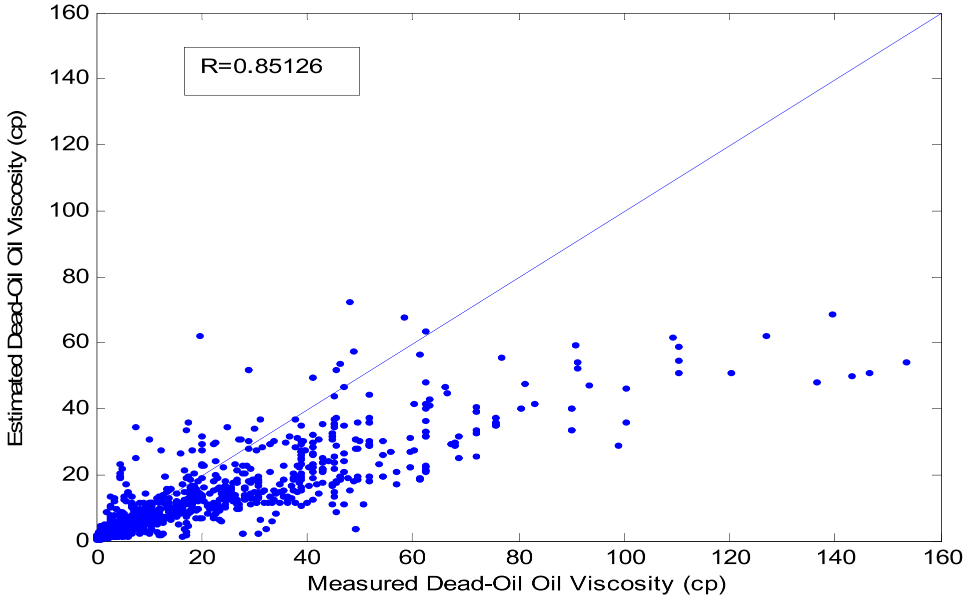

Figure 4-37 Crossplot for Dead-Oil Viscosity (Beggs and Robinson Correlation)

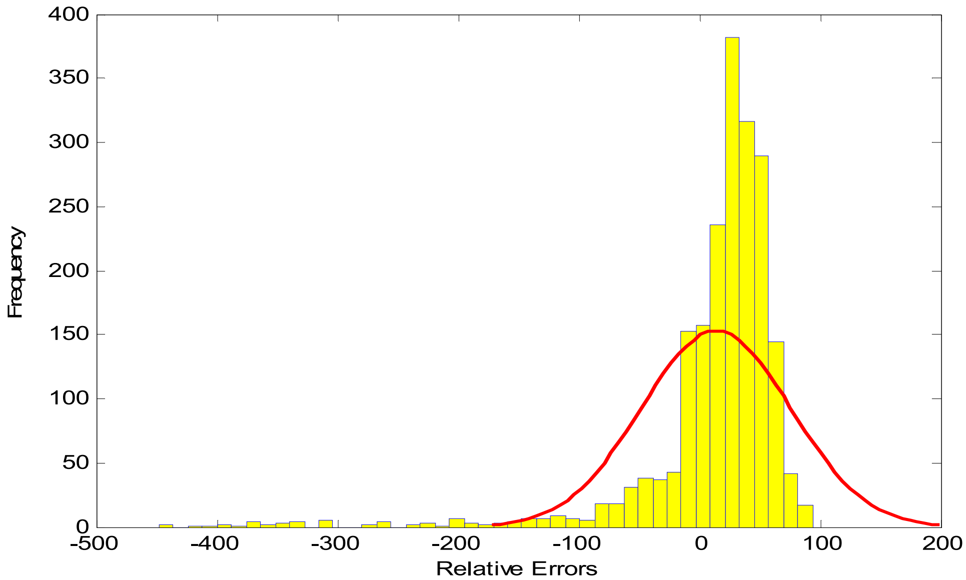

Figure 4-38 Histogram of Errors for Dead-Oil Viscosity (Beggs and Robinson Correlation)

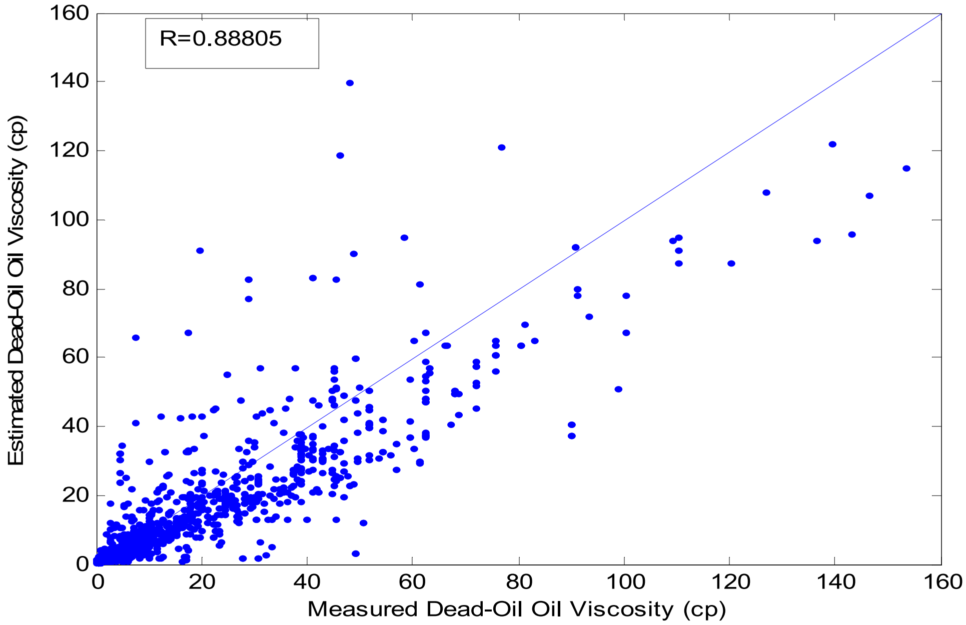

Figure 4-39 Crossplot for Dead-Oil Viscosity (Glaso Correlation)

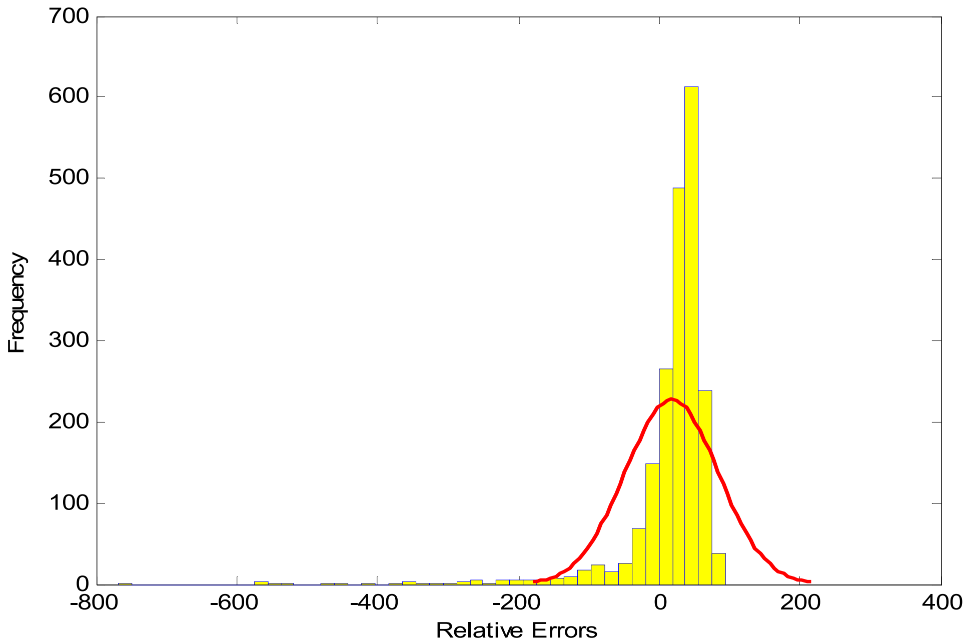

Figure 4-40 Histogram of Errors for Dead-Oil Viscosity (Glaso Correlation)

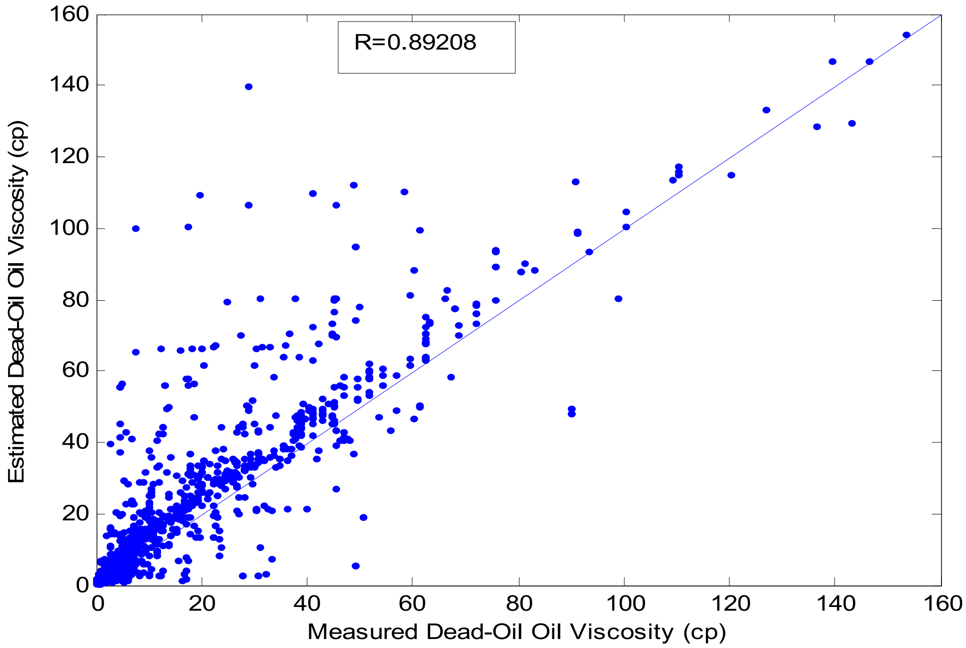

Figure 4-41 Crossplot for Dead-Oil Viscosity (Labedi Correlation)

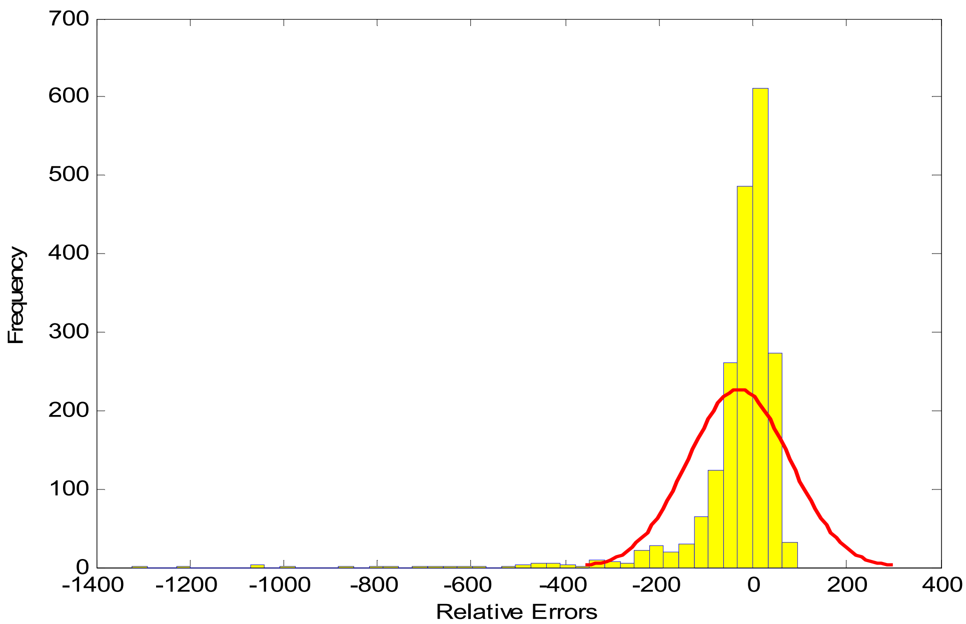

Figure 4-42 Histogram of Errors for Dead-Oil Viscosity (Labedi Correlation)

Chapter 5

Tuning of Existing Correlations for Nigerian Crudes

5.1 Bubblepoint Pressure

Improvement of the existing correlations for PVT properties is another practical step to reduce the error and improve the performance of correlations based on global data sets and as they are applied to crude oil of specific geographical location.

In 1999, Al-Shammasi [23] published a study on the evaluation of Standing, Al-Marhoun, Vasquez and Beggs, Glaso, Kartoatmodjo and Schmidt, Dokla and Osman, Farshad et al, Almehaideb, Lasater, Macary and El Batanoeney, Petrosky and Farshad, and Omar and Todd correlations for bubblepoint pressure using a total of 1243 data sets from 13 different published papers and Kuwait reservoirs. The evaluation examined the performance of correlations with original published coefficients and with recalculated coefficients based on global data sets. Al-Marhoun correlation outperformed other correlation with an average absolute relative error of 19.20 and closely followed by Standing correlation with an average absolute relative error of 20.36.

In 2004, Al-Marhoun [24] published a study on the evaluation of the most frequently used PVT empirical correlations using Middle East data. The study determined the best correlation for the estimation of bubblepoint pressure. He also generated new coefficients for the existing correlations using Middle East data thereby reducing their errors. Standing, Al-Marhoun, Vasquez and Beggs correlations were studied. The results of modified correlation shows that Al-Marhoun correlation for bubblepoint pressure performs best with an average absolute relative error of 7.12.

In this study, Standing, Glaso, and Vasquez and Beggs and Al-Marhoun correlations for bubblepoint pressure coefficients were recalculated using non-linear regression analysis. Statistical error analysis was used to evaluate the performance of the modified correlations using Nigerian data. The statistical accuracy of bubblepoint pressure is shown in the Table 5-1 and crossplots and histograms of relative error are shown in Figure 5-1-5-8.

As shown in Table 5-1 Glaso performs best with average relative and absolute errors, RMS and coefficient of -2.579 11.19, 15.85, and 0.89 respectively. This performance is closely followed by Al-Marhoun, Vasquez and Beggs, then Standing,. Crossplots and Histogram plots Figures 5-1 to 5-8 for all correlations indicate that all correlations overpredict at bubblepoint pressure less than 2000 psia.

Table 5-1 Statistical Accuracy of Pb (Modified)

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Standing(1947)	-1.36	11.85	0.005	87.28	16.36	0.87	-0.32	5.03
Glaso(1980)	-2.56	11.19	0.012	77.69	15.85	0.89	-0.09	5.52
Vasquez and Beggs(1980)	-3.106	11.63	0.0044	102.45	17.02	0.85	-0.934	7.57
Al-Marhoun(1988)	-1.30	11.42	0.014	81.71	15.96	0.88	-0.26	5.26

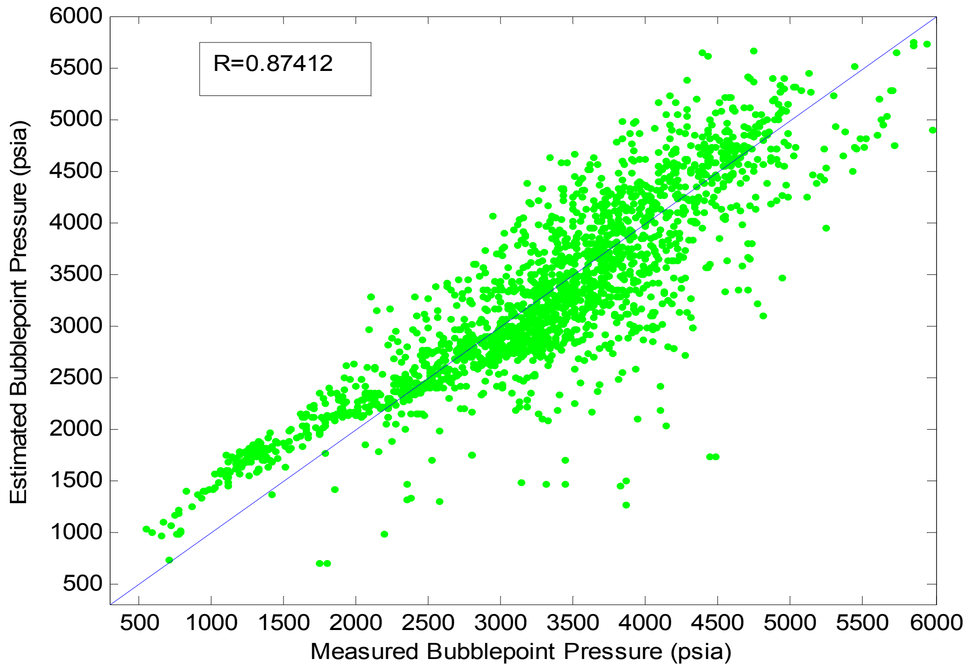

Figure 5-1 Crossplot for Pb (Standing Correlation-Modified)

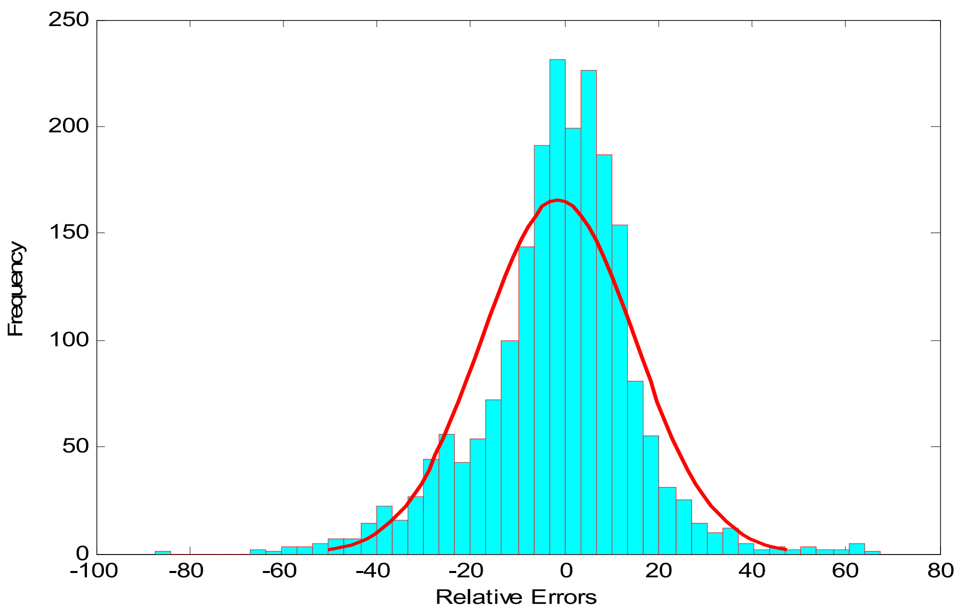

Figure 5-2 Histogram of Errors for Pb (Standing Correlation-Modified)

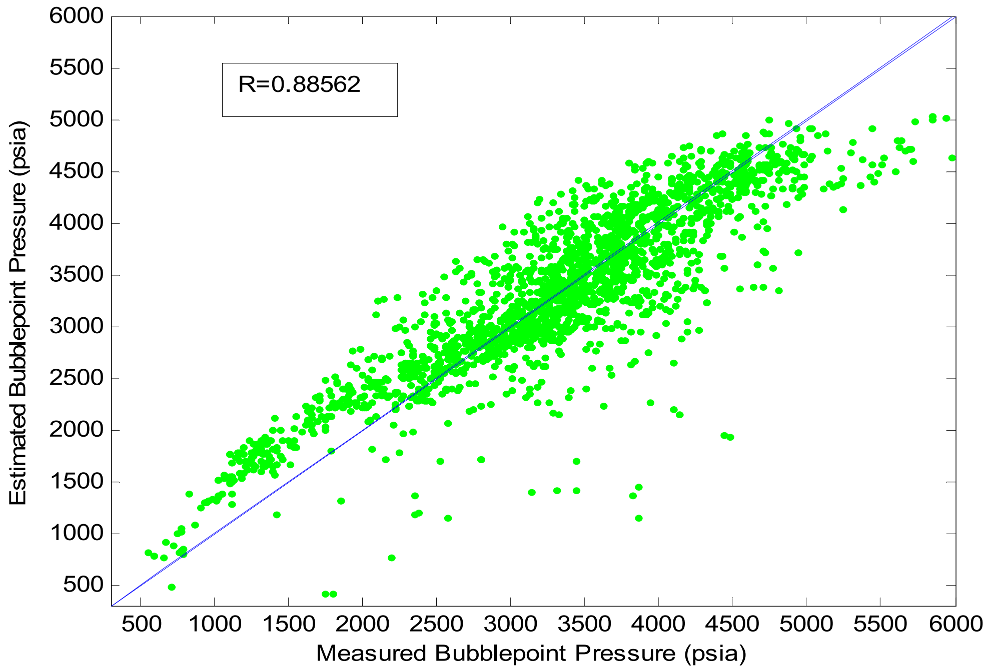

Figure 5-3 Crossplot for Pb (Glaso Correlation-Modified)

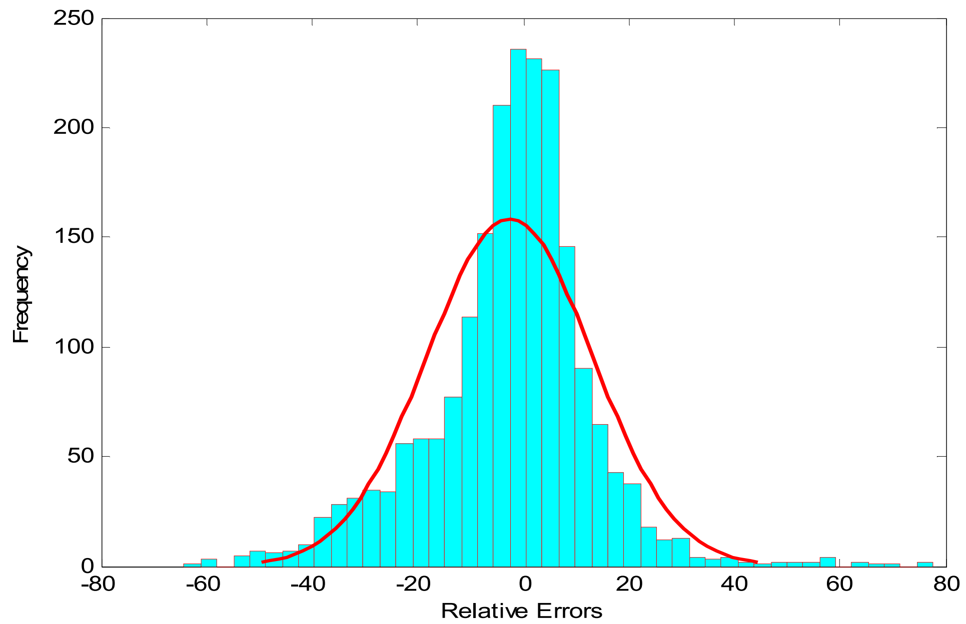

Figure 5-4 Histogram of Errors for Pb (Glaso Correlation-Modified)

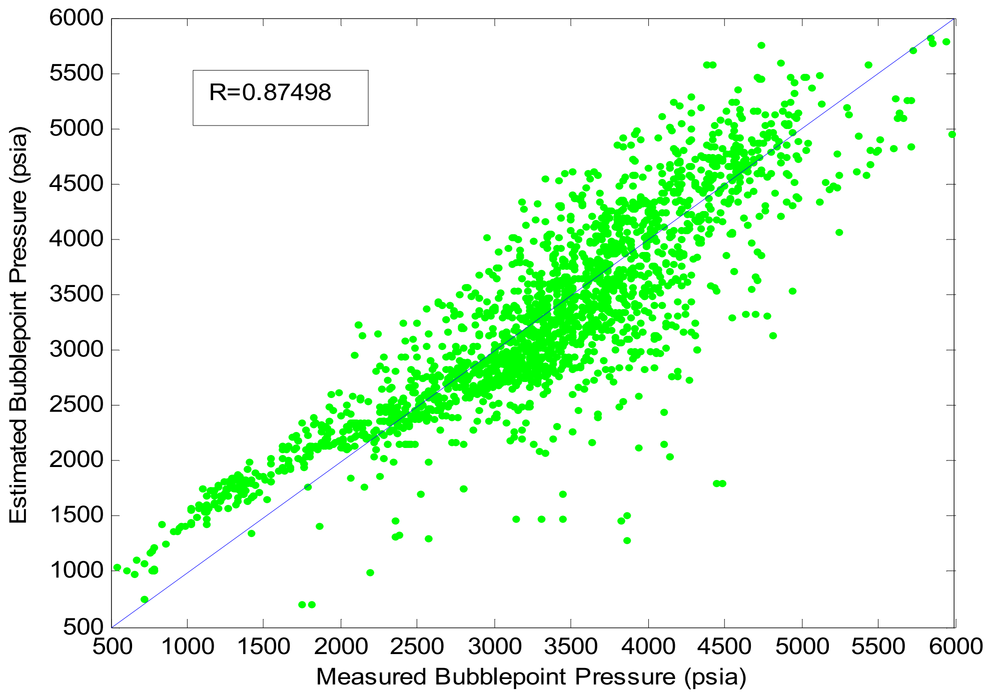

Figure 5-5 Crossplot for Pb (Vasquez & Beggs Correlation- Modified)

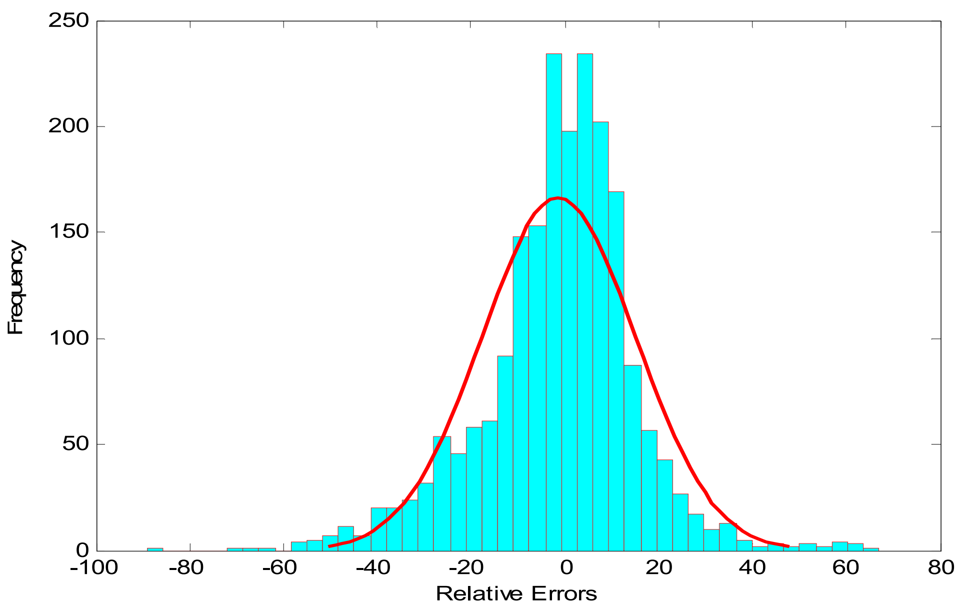

Figure 5-6 Histogram of Errors for Pb (Vasquez & Beggs Correlation-Modified)

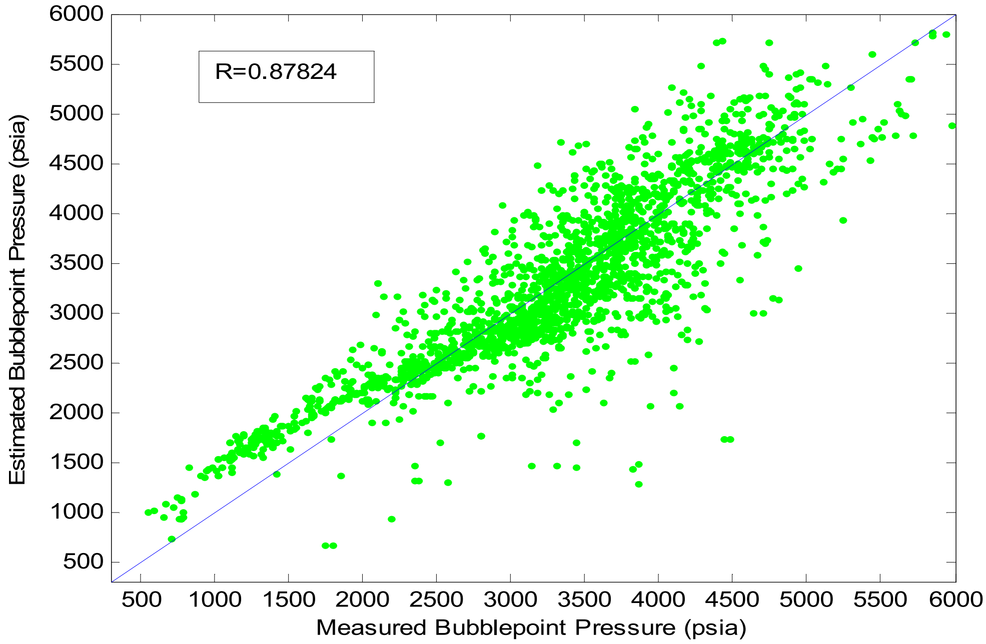

Figure 5-7 Crossplot for Pb (Al-Marhoun Correlation-Modified)

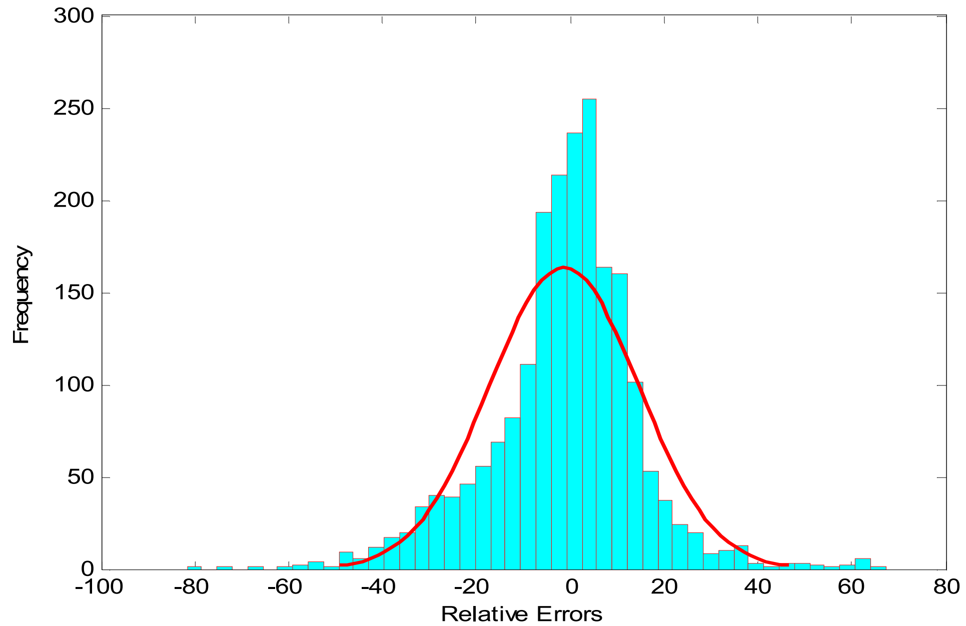

Figure 5-8 Histogram of Errors for Pb (Al-Marhoun Correlation-Modified)

5.2 Solution Gas-Oil Ratio

In 2004, Al-Marhoun [24] published a study on the evaluation of the most frequently used PVT empirical correlations to determine the best correlation for estimation of solution GOR for Middle East crudes. He also generated new coefficients for the existing correlations using Middle East data thereby reducing their errors. Standing, Al-Marhoun, Vasquez and Beggs correlations were studied. The results of modified correlation shows that Al-Marhoun (1988) performs best with an average absolute relative error of 9.20.

In this study, Standing, Al-Marhoun, and Vasquez and Beggs correlations for solution GOR coefficients were recalculated using non-linear regression analysis using Nigerian data. Statistical error analysis was used to evaluate the performance of the modified correlations. The statistical accuracy of solution GOR is shown in the Table 5-2 and crossplots and histograms of relative error are shown in Figure 5-9-5-16.

From Table 5-2 Glaso and Standing correlations give the best performance with average relative absolute errors 16.46 and 16.51 respectively. This performance is closely followed by Vasquez and Beggs (1980). Crossplots for the correlations are shown in the Figures 5-9, 5-11, and 5-13 and 5-15. Histogram plots for all correlations as shown in Figures 5-10, 5-12, 5-14 and 5-16 indicate that they are all negatively skewed.

Table 5-2 Statistical Accuracy of Solution GOR (Modified)

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Standing(1947)	-1.12	16.51	0.000	446.8	33.26	0.91	-6.46	66.80
Glaso(1980)	-3.67	16.46	0.0158	404.1	32.5	0.93	-5.975	58.47
Vasquez and Beggs(1980)	-4.39	17.5	0.0024	490.21	37.00	0.89	-6.936	74.89
Al-Marhoun(1988)	-7.44	20.07	0.008	506.5	38.43	0.90	-6.12	63.39

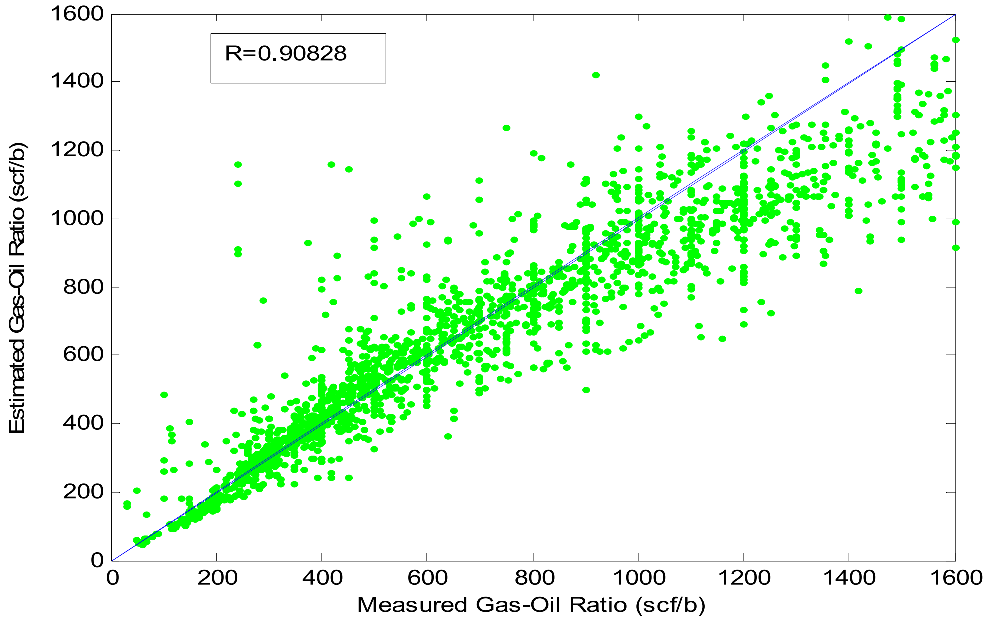

Figure 5-9 Crossplot for Solution GOR (Standing Correlation-Modified)

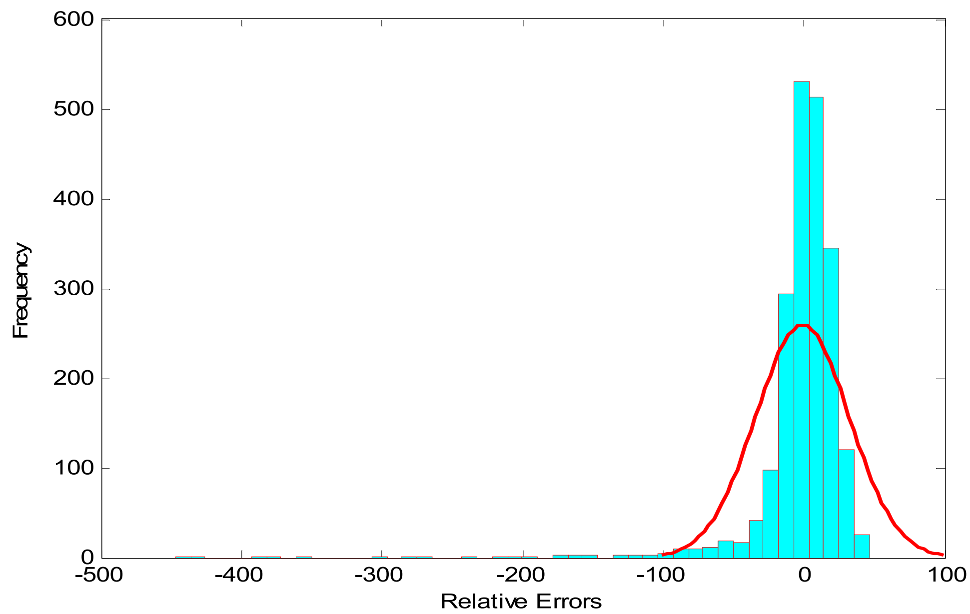

Figure 5-10 Histogram of Errors for Solution GOR (Standing Correlation-Modified)

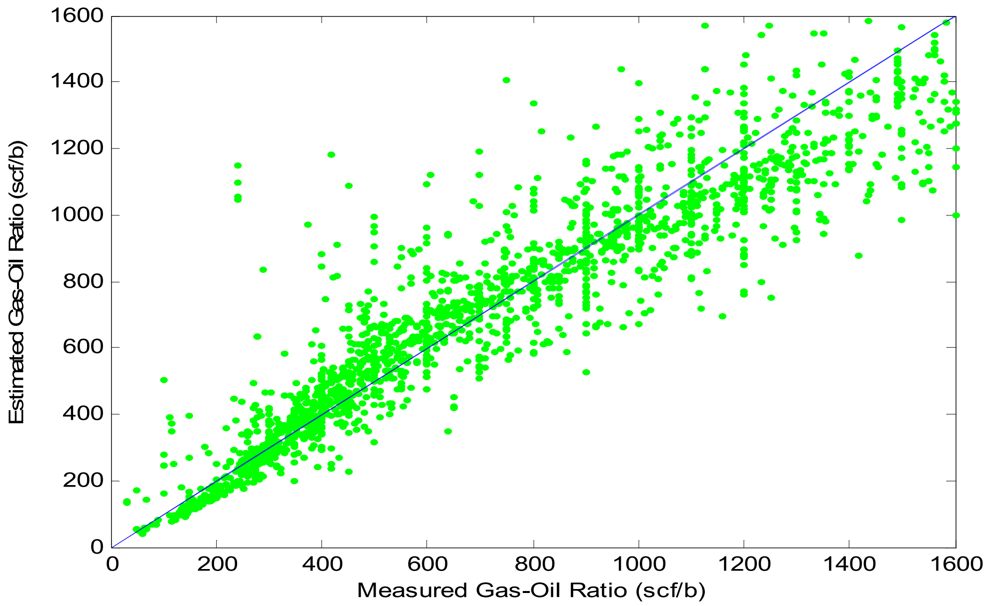

Figure 5-11 Crossplot for Solution GOR (Glaso Correlation-Modified)

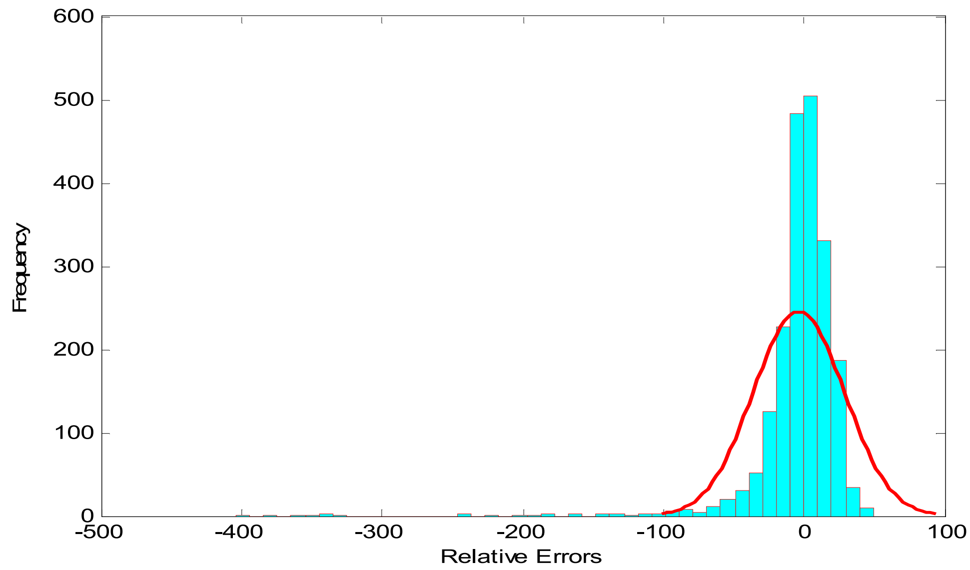

Figure 5-12 Histogram of Errors for Solution GOR (Glaso Correlation-Modified)

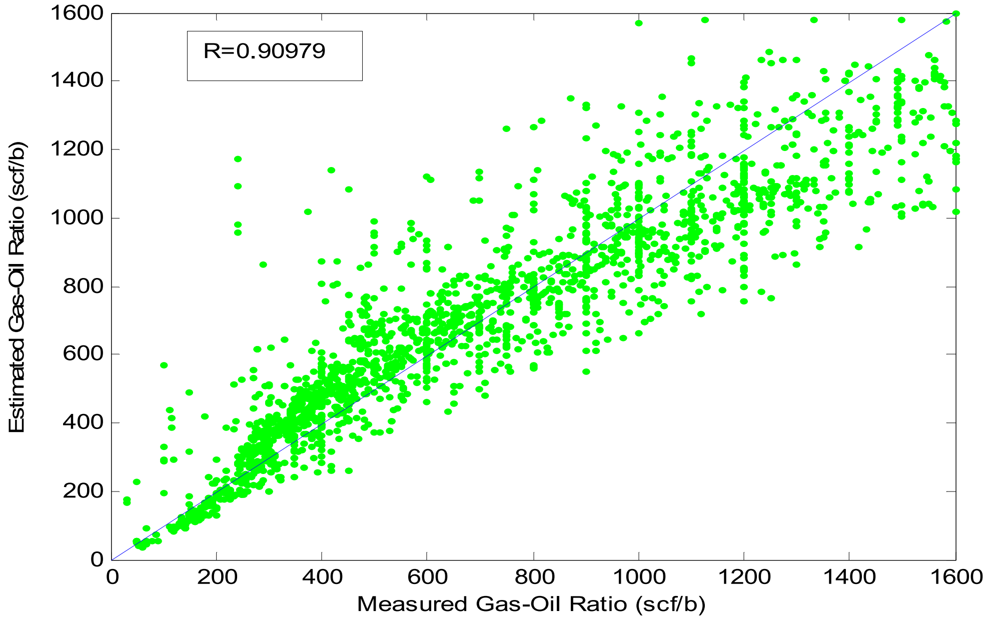

Figure 5-13 Crossplot for Solution GOR (Vasquez & Beggs Correlation-Modified)

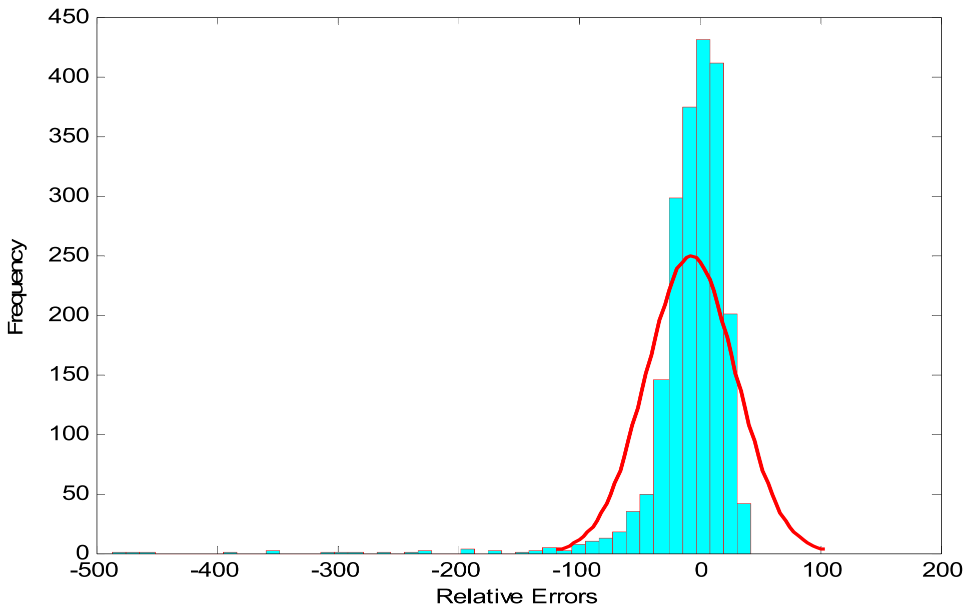

Figure 5-14 Histogram of Errors for Solution GOR (Vasquez & Beggs Correlation-Modified)

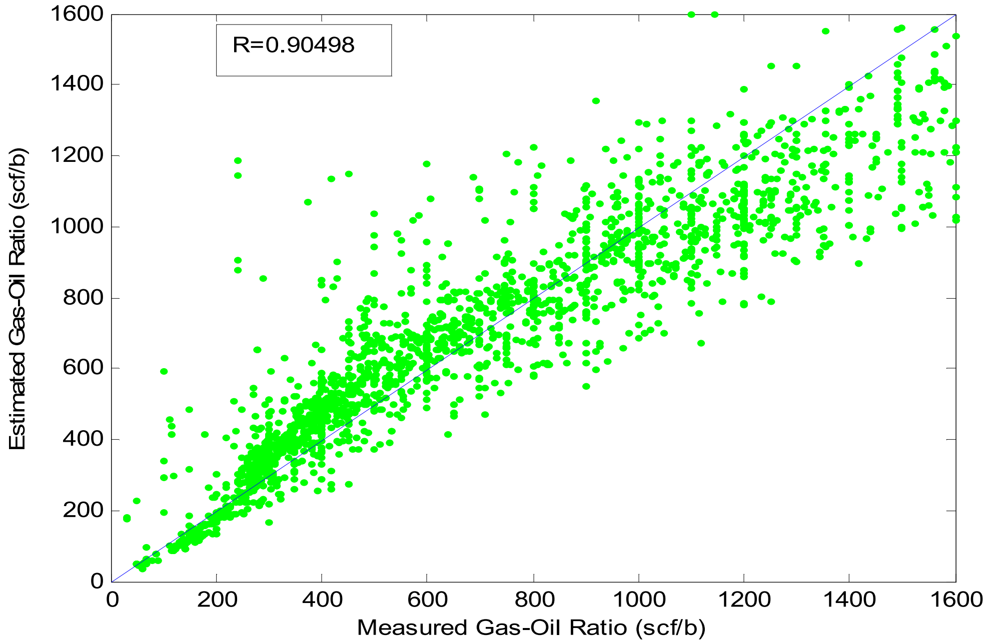

Figure 5-15 Crossplot for Solution GOR (Al-Marhoun Correlation-Modified)

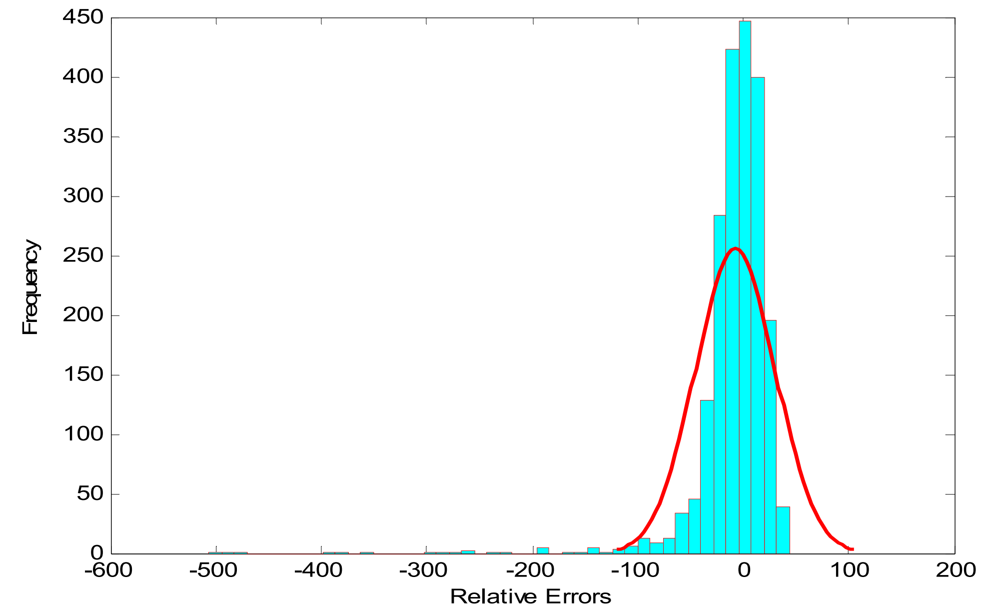

Figure 5-16 Histogram of Errors for Solution GOR (Al-Marhoun Correlation-Modified)

5.3 Oil Formation Volume Factor At Bubblepoint

In 1999, Al-Shammasi [23] published a study on the evaluation of published correlations on oil formation volume factor at bubblepoint based on global data. The evaluation examined the performance of correlations with original published coefficients and with recalculated coefficients based on global data sets. Petrosky and Farshad correlation and Kartoatmodjo and Schmidt correlation for oil formation volume factor converge to the same answer for the recalculation of coefficients based on the global data set. Average absolute relative error of 1.76 was reported for the two correlations. The two correlations are best with new coefficients.

In 2004, Al-Marhoun [24] published a study on the evaluation of the most frequently used PVT empirical correlations to determine oil formation volume factor at bubblepoint for Middle East crudes. He also generated new coefficients for the existing correlations using Middle East data thereby reducing their errors. All of the selected correlations perform well with modified correlations' coefficients. There is a major improvement in errors. Al-Marhoun (1992) correlation was recommended for the data used due to its least average absolute relative error of 0.72.

In this study, Standing, Glaso, Al-Marhoun, and Vasquez and Beggs, and Petrosky and Farshad correlations for oil FVF at bubblepoint coefficients were recalculated using linear regression analysis. Statistical error analysis was used to evaluate the performance of the modified correlations. The statistical accuracy of oil FVF at bubblepoint pressure is shown in the Table 5-3 and crossplots and histograms of relative error are shown in Figure 5-17-5-26.

In Table 5-3 Al-Marhoun (1992) and Vasquez and Beggs show the most outstanding performance. Vasquez and Beggs, and Petrosky and Farshad correlations have average relative absolute error of 2.59 and 2.60 respectively compared with Al-Marhoun with average relative absolute error of 2.58. Al-Marhoun has the least variance and the highest R. Besides, Al-Marhoun error distribution shows highest kurtosis of 16.02. Crossplots and Histograms are shown in Figures 5-17 to 5-26. Standing correlation error distribution shows highest value for variance and the least value 11.611 for kurtosis and is the most normally distributed compare to other correlations with skewness of 0.34.

Table 5-3 Statistical Accuracy of Oil FVF at Pb (Modified)

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Standing(1947)	0.30	3.10	0.000	43.83	4.60	0.95	0.34	11.61
Glaso(1980)	-0.379	3.097	0.0012	41.73	4.37	0.96	0.97	12.33
Vasquez and Beggs(1980)	-0.14	2.59	0.0057	42.95	3.60	0.88	2.185	30.37
Al-Marhoun(1992)	-0.26	2.58	0.001	41.8	4.00	0.97	0.91	16.02
Petrosky & Farshad(1993)	-0.176	2.60	0.0007	42.763	4.0522	0.96	0.80	16.167

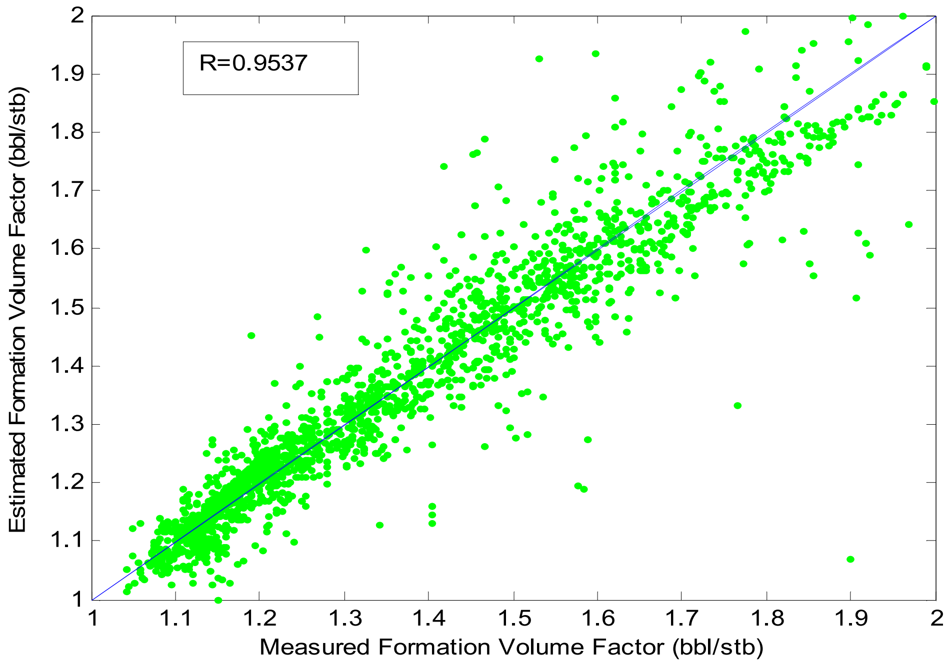

Figure 5-17 Crossplot for Oil FVF at Pb (Standing Correlation-Modified)

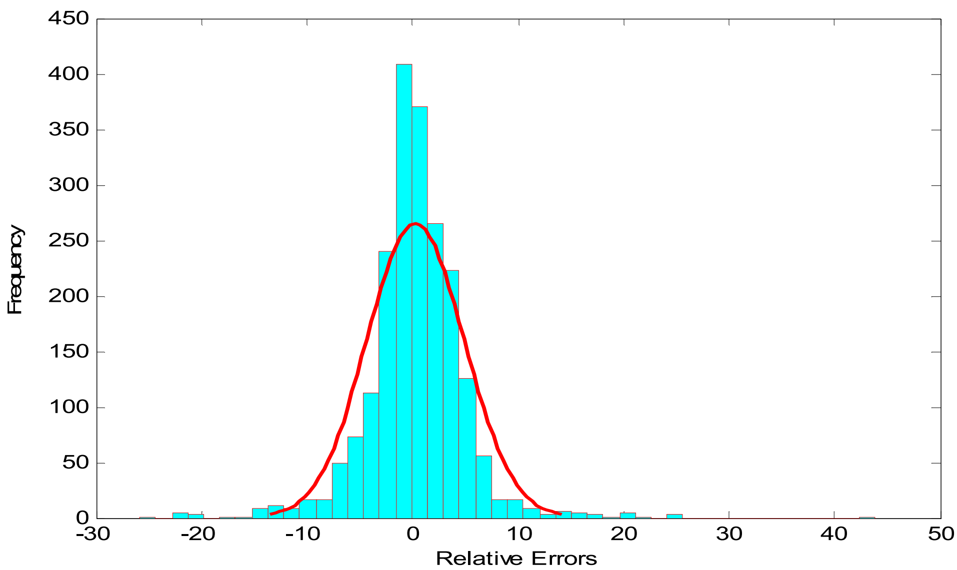

Figure 5-18 Histogram of Errors for Oil FVF at Pb (Standing Correlation-Modified)

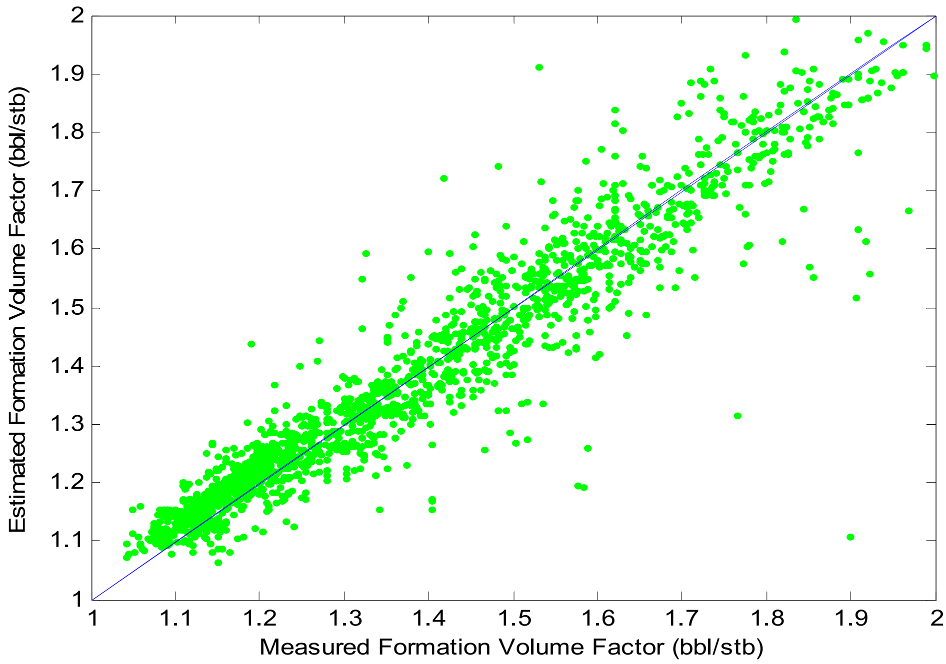

Figure 5-19 Crossplot for Oil FVF at Pb (Standing Correlation-Modified)

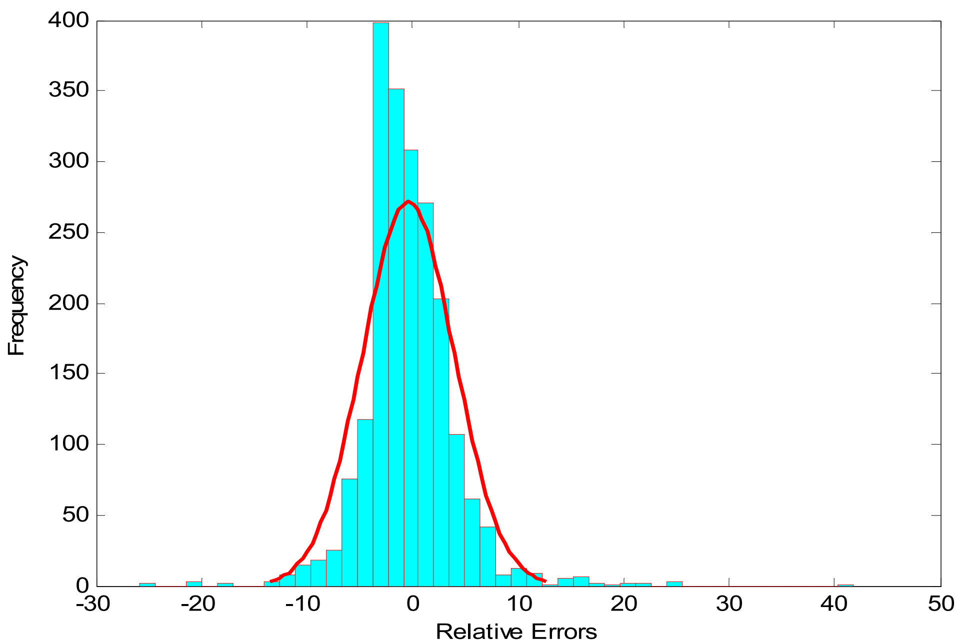

Figure 5-20 Histogram of Errors for Oil FVF at Pb (Glaso Correlation-Modified)

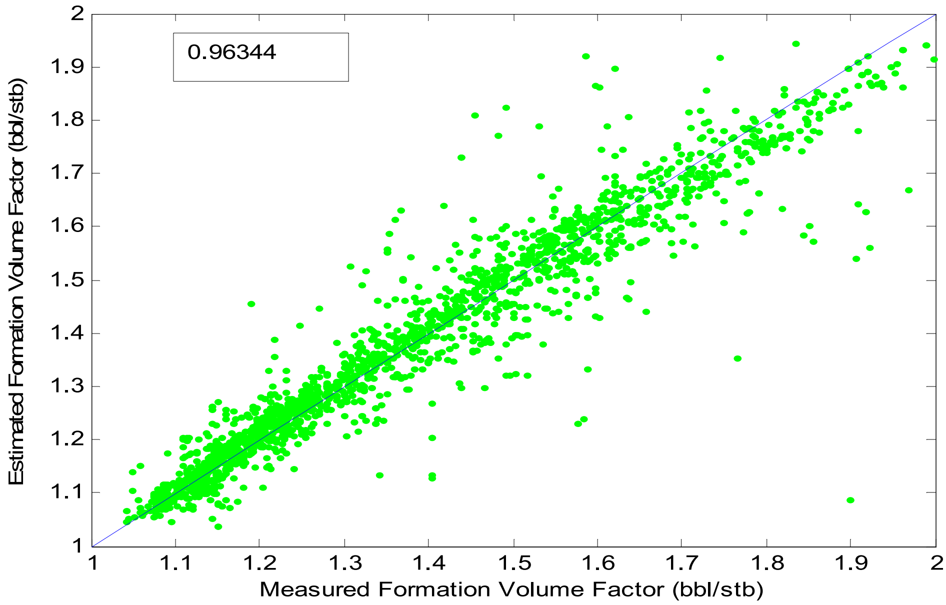

Figure 5-21 Crossplot for Oil FVF at Pb (Vasquez &Beggs Correlation-Modified)

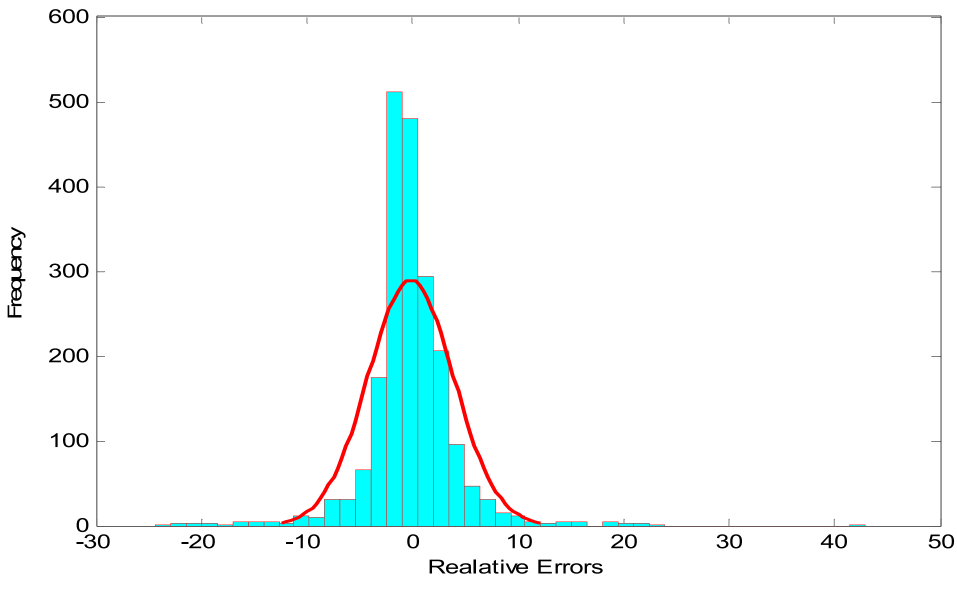

Figure 5-22 Histogram of Errors for Oil FVF at Pb (Vasquez &Beggs Correlation-Modified)

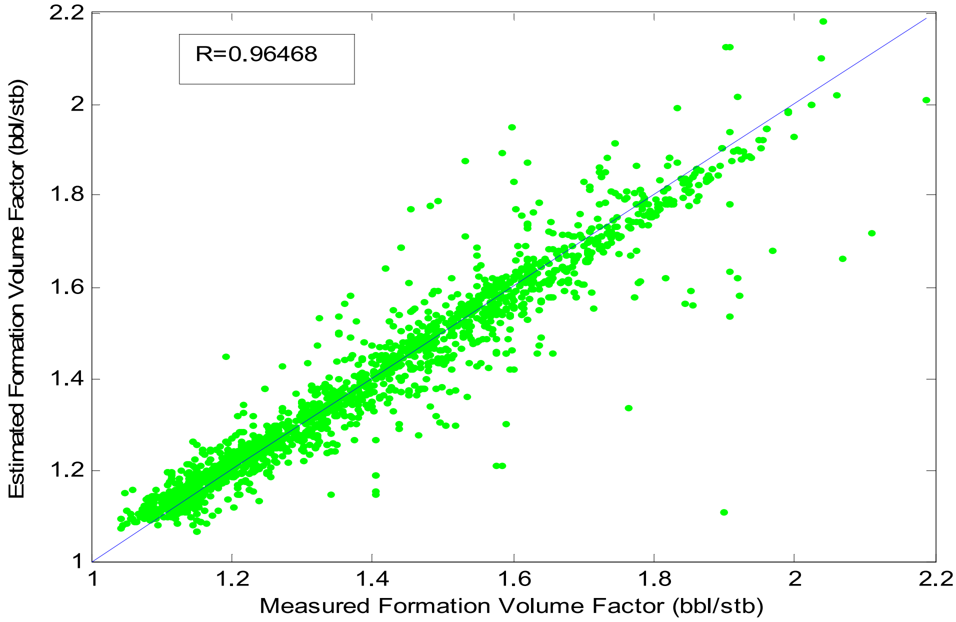

Figure 5-23 Crossplot for Oil FVF at Pb (Al-Marhoun Correlation-Modified)

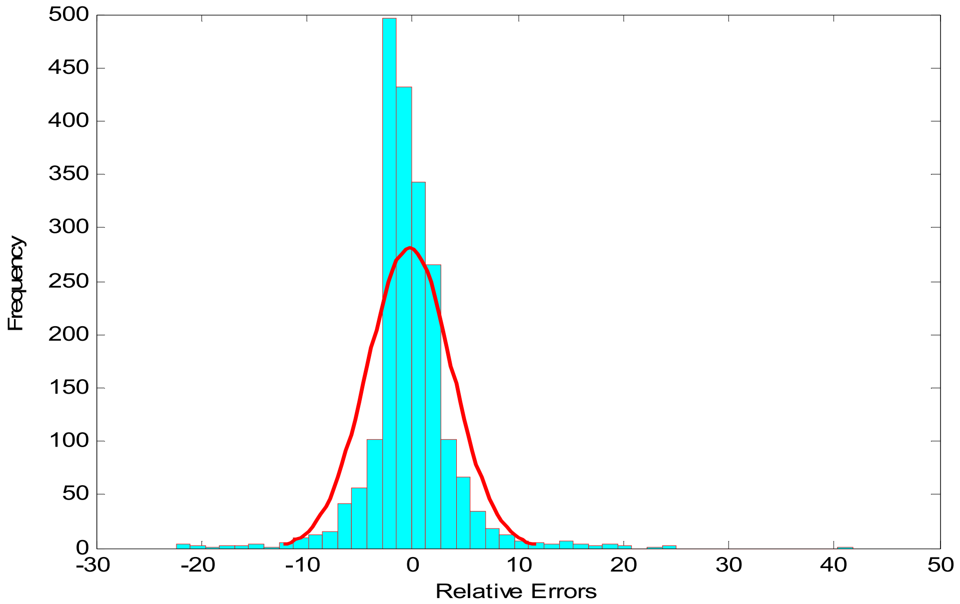

Figure 5-24 Histogram of Errors for Oil FVF at Pb (Al-Marhoun Correlation-Modified)

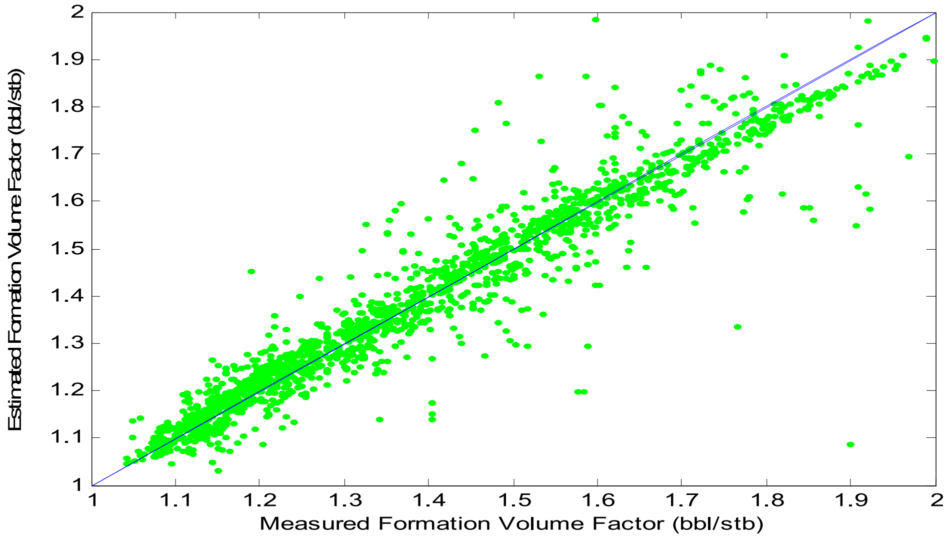

Figure 5-25 Crossplot for Oil FVF at Pb (Petrosky & Farshad Correlation-Modified)

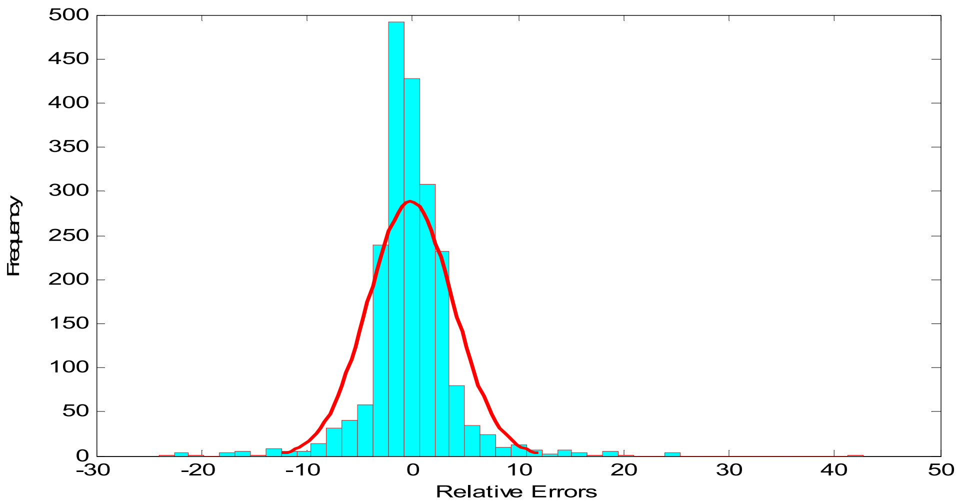

Figure 5-26 Histogram of Errors for Oil FVF at Pb (Petrosky & Farshad Correlation-Modified)

5.4 Oil Viscosity At Bubblepoint

In 2004, Al-Marhoun [24] published a study on the evaluation of oil viscosity at bubblepoint pressure correlations to determine the most accurate one for Middle East crudes. He also generated new coefficients for the existing correlations using Middle East data thereby reducing their errors. Chew and Connally [13], Beggs and Robinson [14], Labedi [17] were studied. All of the selected correlations perform well with modified correlations' coefficient. There is a major improvement in Chew and Connally and Labedi correlation. Beggs and Robinson correlation was recommended for the data used due its least average absolute relative error of 14.04.

In this study, Chew and Connally, Beggs and Robinson, Labedi and Khan et al correlations for oil viscosity at bubblepoint coefficients were recalculated using non-linear regression analysis. Statistical error analysis was used to evaluate the performance of the modified correlations. The statistical accuracy of oil viscosity at bubblepoint is shown in the Table 5-5 and crossplots and histograms of relative error are shown in Figure 5-27-5-34.

The results shown in the Table 5-5 indicate that Beggs and Robinson correlation predicts better than Chew and Connally, Labedi, and Khan et al correlations with average relative absolute error and RMS of 21.06 and 32.47. This performance is followed by Chew and Connally correlation with average relative absolute error of 22.71. Figures 5-27 to 5-34 show the crossplots and histogram of errors distribution. Except for Khan et al correlation, crossplots for all correlations show that all correlations are predicting better at higher viscosity.

Table 5-4 Statistical Accuracy of Oil viscosity at Pb (Modified)

CORRELATION	Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
Chew & Connally(1959)	-5.34	22.71	0.003	295.6	34.06	0.97	-1.87	15.02
Beggs & Robinson(1975)	-6.69	21.06	0.024	251.4	32.47	0.91	-1.66	13.22
Labedi(1992)	8.94	27.03	0.026	302.9	35.29	0.97	-1.22	9.75
Khan et al(1991)	33.45	43.45	0.058	1981	65.81	0.91	-23.05	792.46

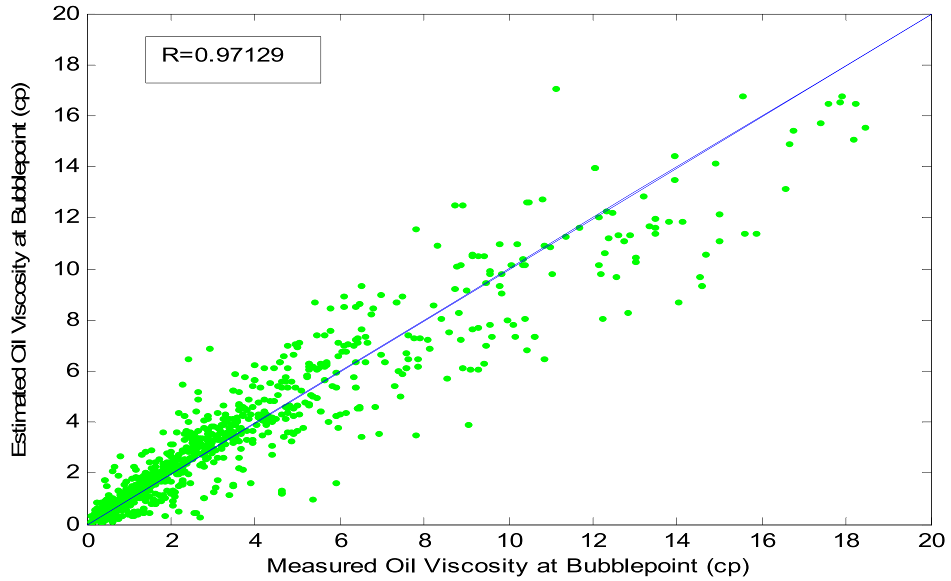

Figure 5-27 Crossplot for Oil Viscosity at Pb (Chew & Connally Correlation-Modified)

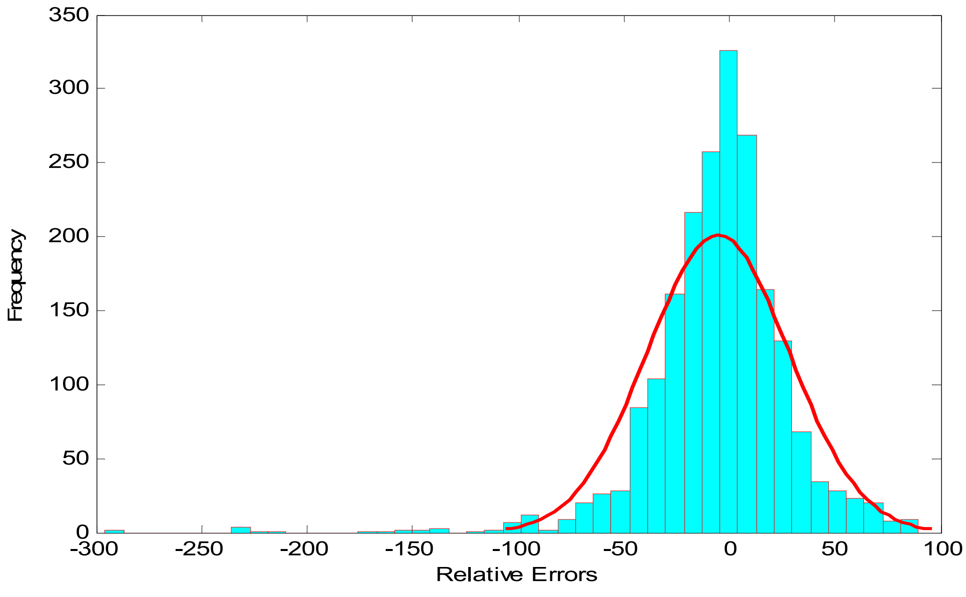

Figure 5-28 Histogram of Errors for Oil Viscosity at Pb (Chew & Connally Correlation-Modified)

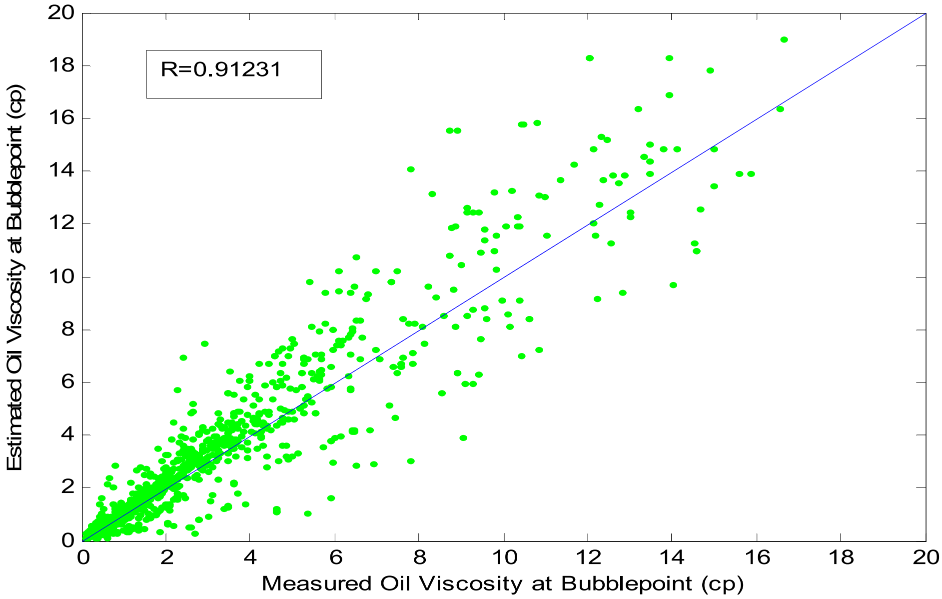

Figure 5-29 Crossplot for Oil Viscosity at Pb (Beggs and Robinson Correlation-Modified)

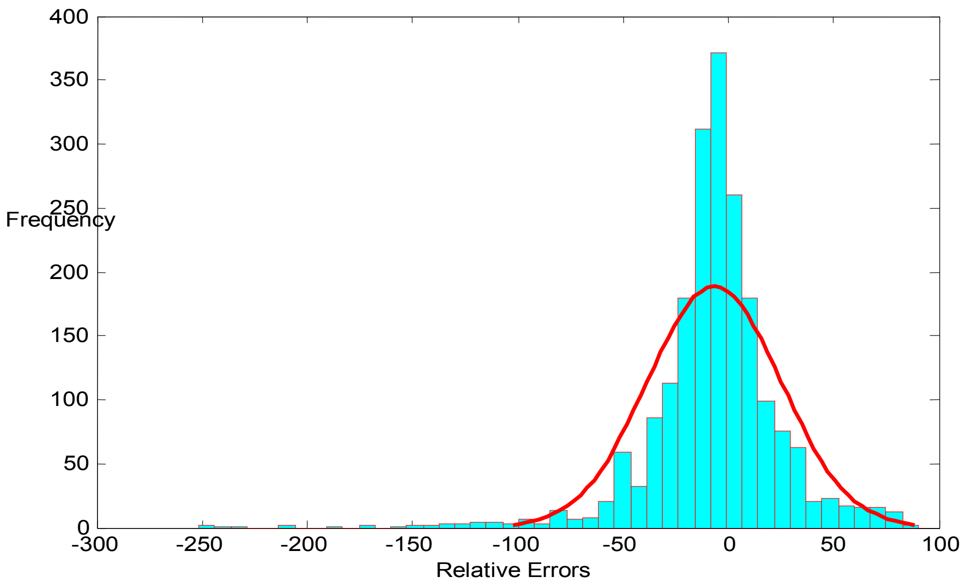

Figure 5-30 Histogram of Errors for Oil Viscosity at Pb (Beggs and Robinson Correlation-Modified)

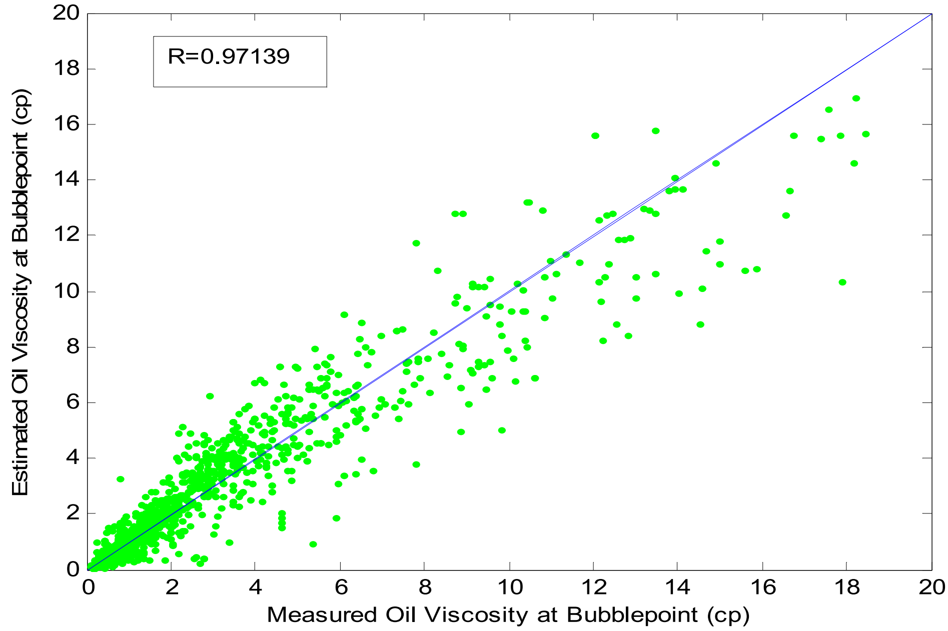

Figure 5-31 Crossplot for Oil Viscosity at Pb (Labedi Correlation-Modified)

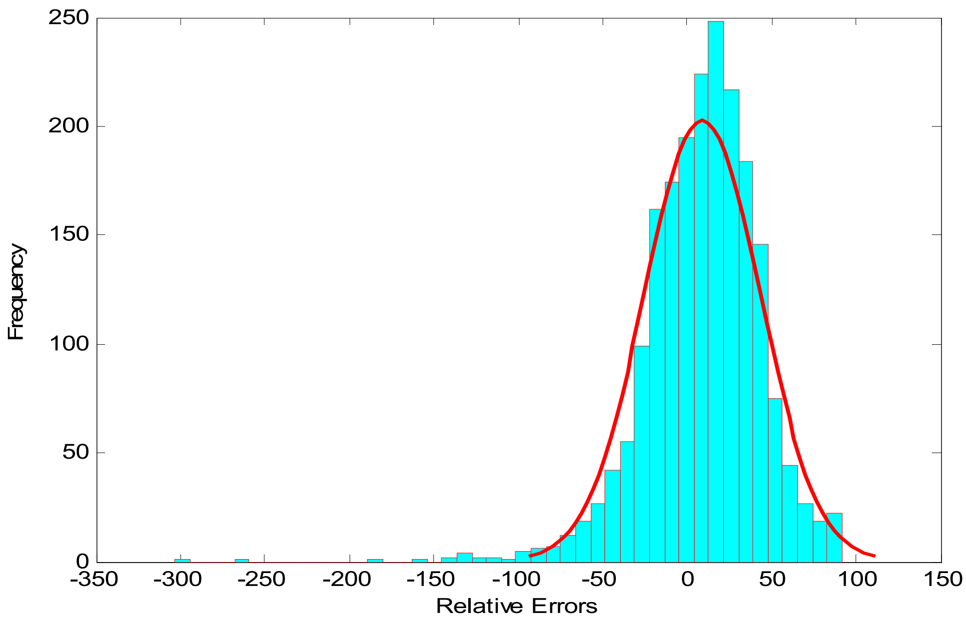

Figure 5-32 Histogram of Errors for Oil Viscosity at Pb (Labedi Correlation-Modified)

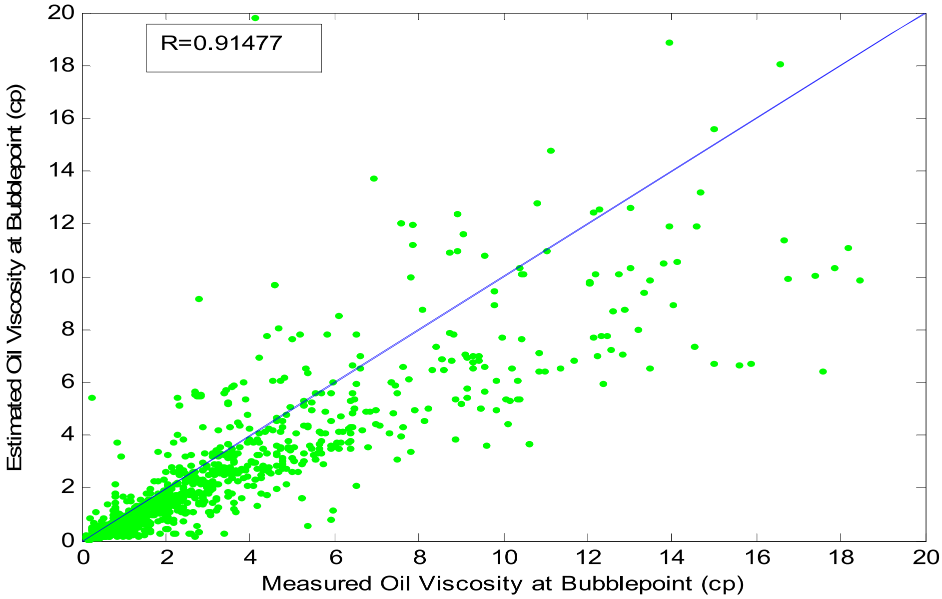

Figure 5-33 Crossplot for Oil Viscosity at Pb (Khan et al Correlation-Modified)

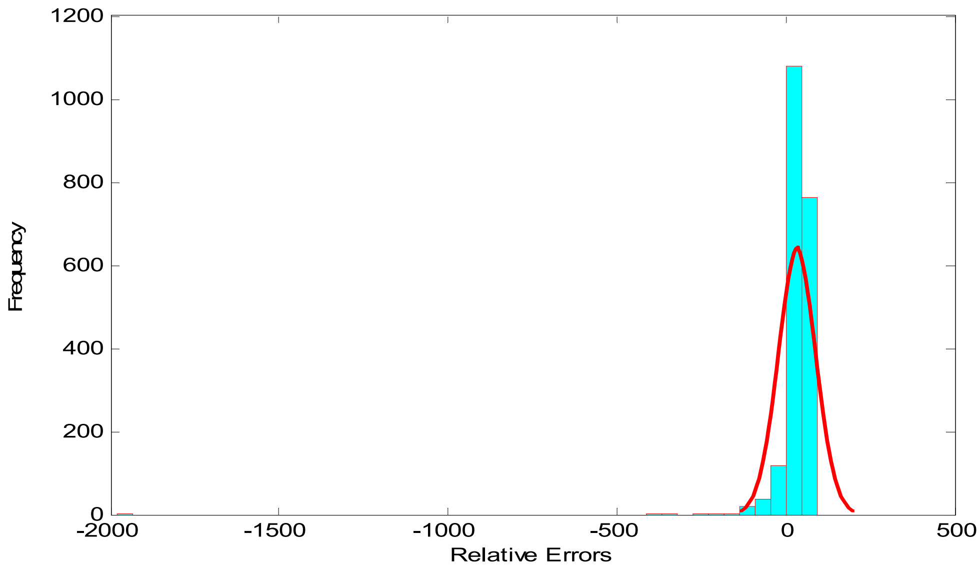

Figure 5-34 Histogram of Errors for Oil Viscosity at Pb (Khan et al Correlation-Modified)

5.5 Dead Oil Viscosity

In 2004, Al-Marhoun [24] published a study on the evaluation of the most frequently used dead-oil viscosity correlations to determine the most accurate for Middle East crudes. He also generated new coefficients for the existing correlations using Middle East data thereby reducing their errors. Chew and Connally [13], Beggs and Robinson [14], Labedi [17] were studied. All of the selected correlations perform well with modified correlations' coefficient. There is a major improvement in Chew and Connally and Labedi correlation. Beggs and Robinson correlation was recommended for the data used due its least average absolute relative error of 14.04.

In this study, Beal, Beggs and Robinson, Glaso and Labedi correlations for dead oil viscosity coefficients were recalculated using non-linear regression analysis. Statistical error analysis was used to evaluate the performance of the modified correlations. The statistical accuracy of dead-oil viscosity is shown in the Table 5-5 and crossplots and histograms of relative error are shown in Figure 5-35-5-42.

As indicated in Table 5-5, there is no much improvement in the performance of these correlations with recalculated coefficients. Beal has shown no improvement at all. Glaso correlation performs best. Glaso correlation better performance is shown by the relative absolute error and correlation coefficient of 41.42 and 0.89 respectively. The crossplots and histograms of error are shown in Figures 5-35 to 5-42. As shown in Table 5-5 all the correlations are negatively skewed and are not normally distributed.

Table 5-5 Statistical Accuracy of Dead-Oil Viscosity (Modified)

CORRELATION	Er	Ea	Emin	Emax	RMS	R	VAR	SKEWNESS	KURTOSIS
Beal(1946)	-19.32	42.84	0.002	905.7	91.84	0.89	8066.1	-4.67	32.69
Beggs & Robinson(1975)	-7.65	42.09	0.024	928.2	85.21	0.89	7063.5	-4.97	37.33
Glaso(1980)	-20.05	41.15	0.023	932.3	94.44	0.89	8497.3	-4.95	35.65
Labedi(1992)	5.63	46.22	0.003	956.9	82.58	0.89	6791.1	-5.33	45.64

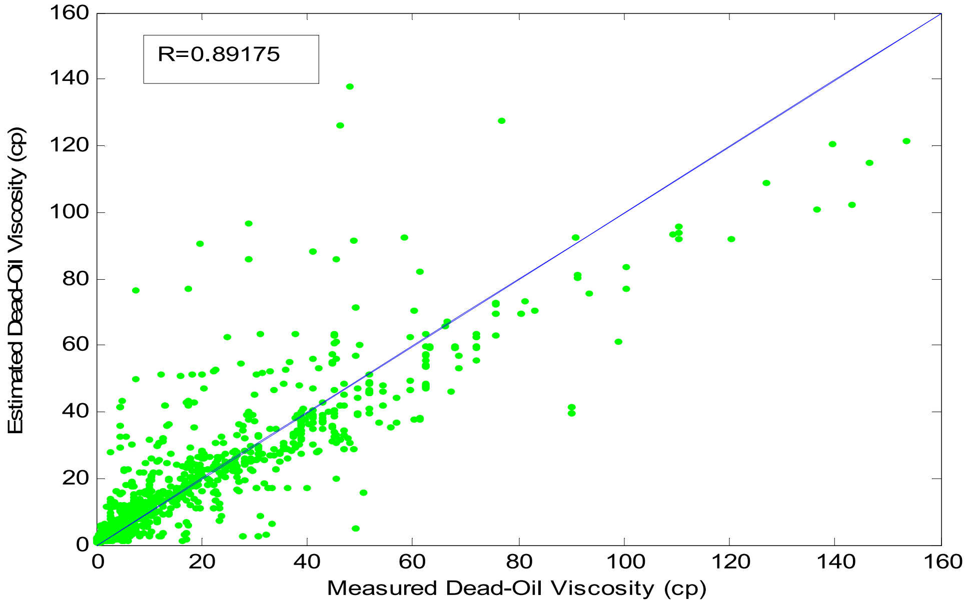

Figure 5-35 Crossplot for Dead-Oil Viscosity (Beal Correlation-Modified)

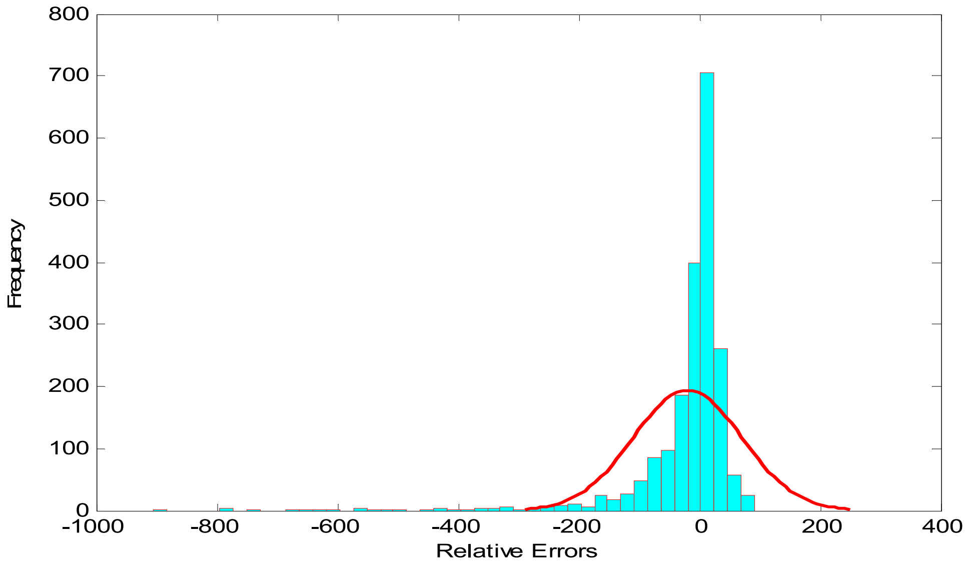

Figure 5-36 Histogram of Errors for Dead-Oil Viscosity (Beal Correlation-Modified)

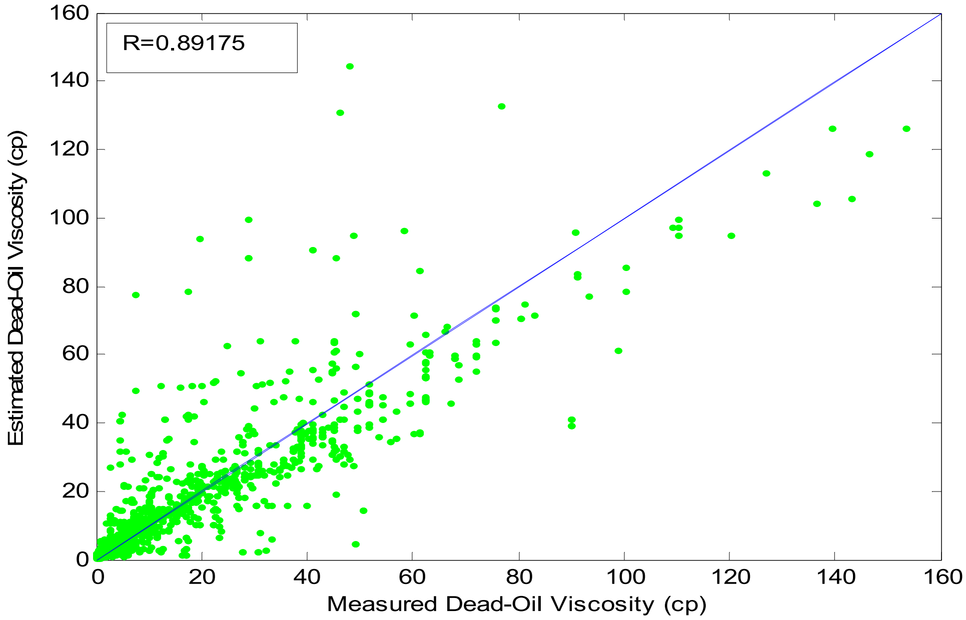

Figure 5-37 Crossplot for Dead-Oil Viscosity (Beggs & Robinson Correlation-Modified)

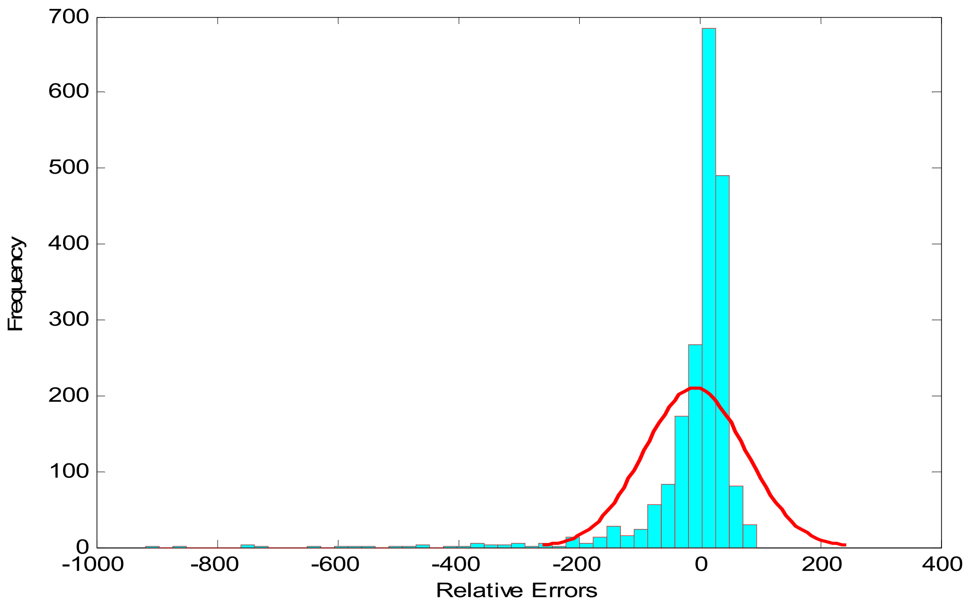

Figure 5-38 Histogram of Errors for Dead-Oil Viscosity (Beggs & Robinson Correlation-Modified)

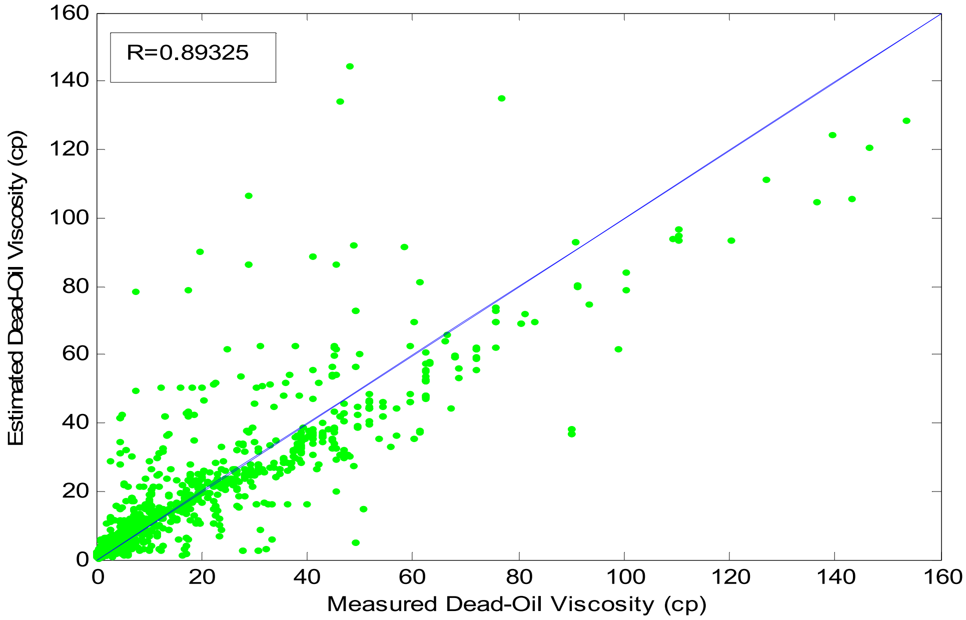

Figure 5-39 Crossplot for Dead-Oil Viscosity (Glaso Correlation-Modified)

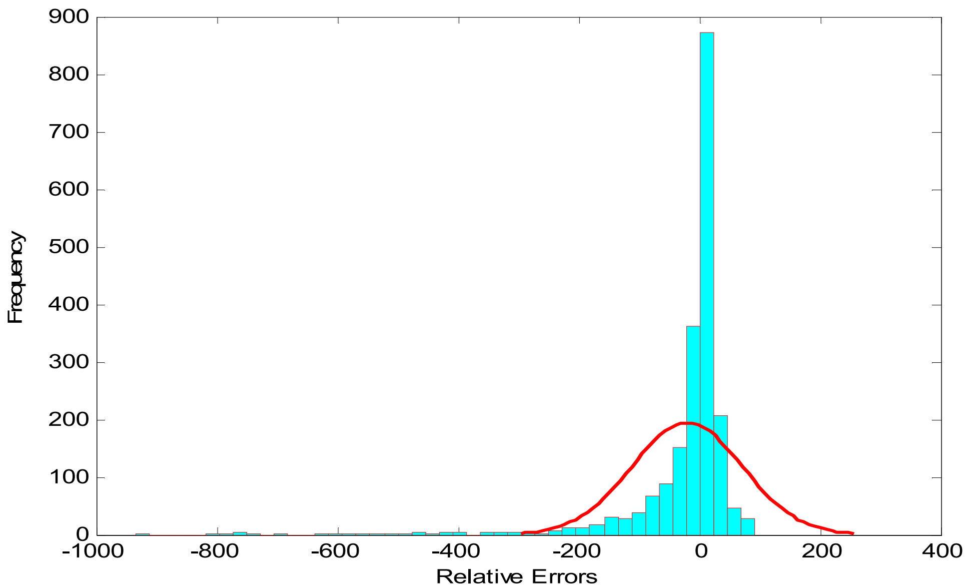

Figure 5-40 Histogram of Errors for Dead-Oil Viscosity (Glaso Correlation-Modified)

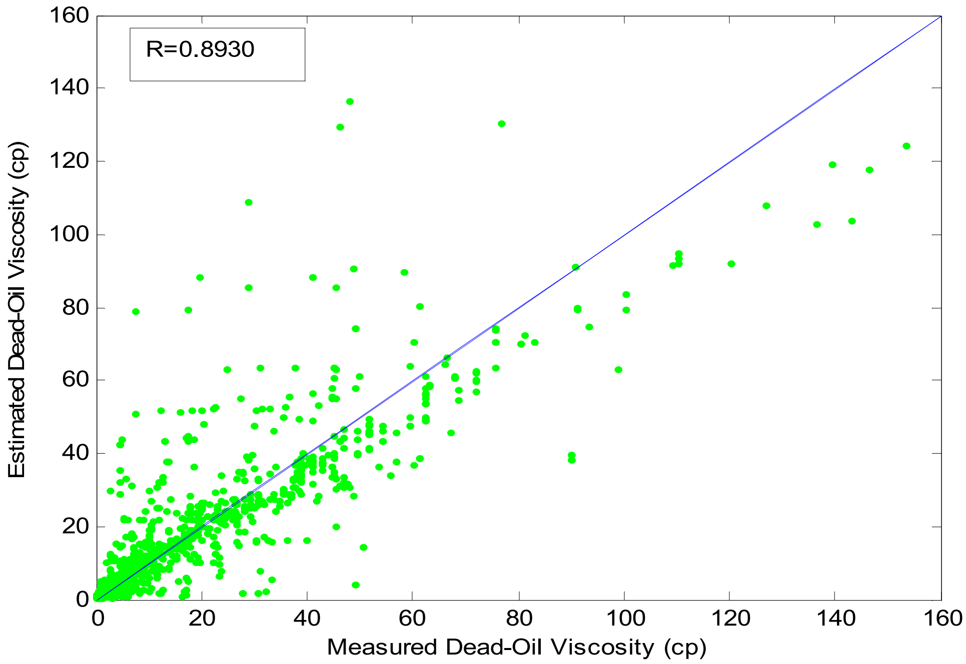

Figure 5-41 Crossplot for Dead-Oil Viscosity (Labedi Correlation-Modified)

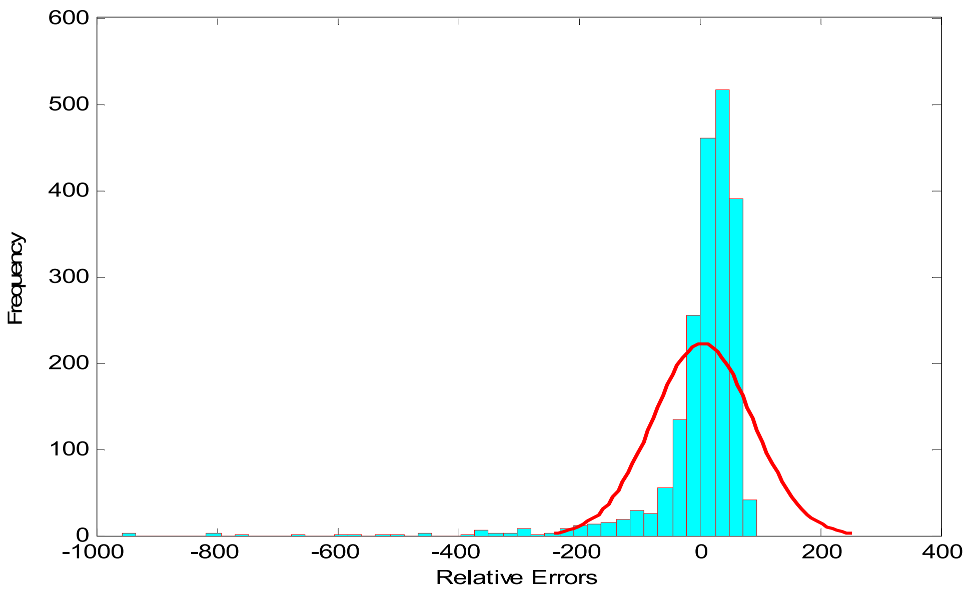

Figure 5-42 Histogram of Errors for Dead-Oil Viscosity (Labedi Correlation-Modified)

Chapter 6

PVT Models Using Artificial Neural Networks

6.1 The Use of Neural Networks in Petroleum Engineering

Artificial neural networks (ANN) has been defined as a computer model that attempts to mimic simple biological learning process and simulate specific functions of human nervous system [25].

Artificial neural networks is a simple arrangement of nodes, called neurons, used for pattern recognition, modeled after a representation of human brain, is a new computation strategy one may apply to old problems that have already been solved , to see whether it can yield more rapid or efficient solution. It could also be applied to the old unsolved problems. In the same vein, it could be applied to new problems [27]. Neural network is an alternative computational approach based on theory of human brain and intelligence. It solves problems by example rather than by following a set of heuristics or theoretical mechanisms [26]. ANN may be thought of as a nonparametric, nonlinear regression technique.

The use of ANN in Petroleum Industry has over the years become popular and more efficient. Many attempts have been reported in literature by different authors on the use of ANN to solve Petroleum Engineering problems [27].

ANN is capable of learning in order to recognize, classify and generalize. The learning process can be supervised, in which case, the input and output patterns are required or be un-supervised, which requires only the input patterns [25].

6.2 Neuron

A neuron is one of the most important components of the network. It processes and analyzes information pertinent to prediction and generalization. A neuron gathers the information from the preceding neuron and forwards its output to the neurons in the following layer. Figure 6-1 shows a typical neuron. The sum of the previous input (x_i) and its corresponding weights (w_i) are received by a neuron in the next layer. This neuron will process this information by applying the activation function on the sum to generate an output for the neuron. The output is then passed to a neuron in the next layer. There are four major components which make up an artificial neuron. These components are weighting factors, summation factors, transfer function and activation function.

6.2.1 Weighting Factors

A neuron usually receives many simultaneous inputs. Each input has its own relative weight which gives the input the impact that it needs on the processing element's summation function. These weights perform the same type of function as do the varying synaptic strengths of biological neurons. In both cases, some inputs are made more important than others so that they have a greater effect on the processing element as they combine to produce a neural response.

Weights are adaptive coefficients within the network that determine the intensity of the input signal as registered by the artificial neuron. They are a measure of an input's connection strength. These strengths can be modified in response to various training sets and according to a network's specific topology or through its learning rules.

6.2.2 Summation Function

The first step in a processing element's operation is to compute the weighted sum of all of the inputs. Mathematically, the inputs and the corresponding weights are vectors which can be represented as $x_1, x_2 \ldots\ldots x_n$ and $w_1, w_2 \ldots\ldots w_n$. The total input signal is given by

$$\sum x_i \times w_i \qquad (1)$$

The summation function can be more complex than just the simple input and weight sum of products. The input and weighting coefficients can be combined in many different ways before passing on to the transfer function [25]. In addition to a simple product summing, the summation function can select the minimum, maximum, majority, product, or several normalizing algorithms. The specific algorithm for combining neural inputs is determined by the chosen network architecture and paradigm.

Some summation functions have an additional process applied to the result before it is passed on to the transfer function. This process is sometimes called the activation function. The purpose of utilizing an activation function is to allow the summation output to vary with respect to time. Activation functions currently are pretty much confined to research. Most of the current network implementations use an "identity" activation function, which is equivalent to not having one. Additionally, such a function is likely to be a component of the network as a whole rather than of each individual processing element component.

6.2.3 Transfer Function

The result of the summation function, almost always the weighted sum, is transformed to a working output through an algorithmic process known as the transfer function. In the transfer function the summation total can be compared with some threshold to determine the neural output. If the sum is greater than the threshold value, the processing element generates a signal. If the sum of the input and weight products is less than the threshold, no signal is generated.

The threshold, or transfer function, is generally non-linear. Linear functions are limited because the output is simply proportional to the input. Linear functions are not very useful. The transfer function could be something as simple as depending upon whether the result of the summation function is positive or negative [26]. The network could output zero and one, one and minus one, or other numeric combinations

6.2.4 Activation Function

The activation function is a mathematical function applied to a node's activation that computes the signal strength it outputs to subsequent nodes. It is a function that squashes the output signal in a permissible amplitude range. When a neuron updates it passes the sum of the incoming signals through an activation function, or transfer function (linear or nonlinear). Among the common activation functions used by ANN are; Linear function, Binary function, Probabilistic function, and the Sigmoid function.

6.2.4.1 The Linear Function

This could be identity or linear scaled function. They are used primarily by the input layer so that the input data are passed to the next layer as they are.

i. Identity:

$$f(x) = mx \tag{2}$$

ii. Linear scaled:

$$f(x) = mx + c \tag{3}$$

6.2.4.2 Binary Function

This is used to convert the continuous data into a binary form, which is very useful for categorization of data. It is represented as:

$$f(x) = \begin{cases} 1 & \text{if } x \geq b \\ 0 & \text{if } x < b \end{cases} \tag{4}$$

6.2.4.3 Probabilistic Function

There are two types of probabilistic functions namely Gaussian function and Gaussian complements.

Mathematically, Gaussian:

$$f(x) = e^{-x^2} \tag{5}$$

And, Gaussian complement:

$$f(x) = 1 - e^{-x^2} \tag{6}$$

6.2.4.4 Sigmoid Function

The most popular activation function is the sigmoid logistic function for prediction and generalization. The sigmoid function is a unipolar function, which produces output in the range of (0, 1). This particular function is continuous, therefore, differentiable everywhere with a positive slope. Figure 6-2 shows a sigmond function.

The backpropagation network greatly utilizes the sigmoid function for its transformation processes. The sigmond function is defined as

f(x) = $\frac{1}{1+e^{-x+T}}$ where T is a threshold or transfer value

6.3 Feed-forward, Back-Propagation

Currently, back-propagation architecture is the most popular, and effective, model for complex, multi-layered networks. This network is used more than all other combined. It is a gradient based optimization procedure. It is a supervised learning algorithm which uses data with associated target output to train an ANN. Its greatest strength is in non-linear solutions to problems. In this scheme, the network learns a predefined set of input-output sample pairs by using a two-phase propagate-adapt cycle. After the input data are provided as stimulus to the first layer of network unit, it is propagated through each upper layer until an output is generated. The latter, is then compared to the desired output, and an error signal is computed for each output unit.

The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but typically there is just one or two. The in and out layers indicate the flow of information during recall. Recall is the process of putting input data into a trained network and receiving the answer. Back-propagation is not used during recall, but only when the network is learning a training set. The number of layers and the number of processing element per layer are important decisions. They are the art of the network designer. There is no short cut to a precise format to the layout of the network for any particular application.

6.3.1 Training Process

The overall training of the ANN involves the input values of the first layer are weighted and passed on to the hidden layer; the neurons in the hidden layer will produce outputs by applying an activation function to the sum of the weighted input values; the resulting outputs are then weighted by the connections between the hidden and output layer. The desired results are generated in the output layer. The network achieves the desired learning by adjusting its interconnected weights continuously until there is a close match between the output from the neurons and the "real" or "target" output from the training data. The difference between the predicted outputs and the original outputs is referred to as error.

6.3.2 Cross Validation

The training data set is divided into two groups: the first used to train the network and the second group used for testing the error during training. This helps to prevent the over fitting the training data and to monitor the generalization performance of the network.

6.3.3 Testing

After the Network has been successfully trained well, it is then blind-tested against a set of data withheld from it during its training session. Regression analysis is utilized to measure the degree of identity between the actual output and the network output. A coefficient of correlation (R) of 1 gives an indication of a perfect model while an R of 0 indicates a very bad model.

6.4 The Use of Neutal Network in PVT Modeling

In 1997, Gharbi and Elsharkawy [29] published a neural network study for estimating bubblepoint pressure and oil formation volume factor at bubblepoint. They used network with 2 hidden layers for each property separately. The bubblepoint pressure neural network has 8 neurons in the first layer and 4 neurons in the second layer. Also, oil formation volume factor at bubblepoint has 6 neurons in both first and the second hidden layers. 498 data sets collected from literature and unpublished sources were used to train the network and other 22 data sets were used for testing. The results of this study show improvement over the conventional correlations.

Also in 1997, Gharbi and Elsharkawy [30] presented another neural network model for estimating bubblepoint pressure and oil formation volume factor at bubblepoint for universal use. Their network has only 1 hidden layer with 5 neurons, 4 input nodes, and

2 output nodes. The overall performance was better than any of the published correlations cited. Correlation coefficient for P_b is 0.9891 and for B_{ob} is 0.9875 with Ea of 6.48 and 1.97 respectively.

In 1998, Elsharkawy [31] published a neural network model to estimate PVT parameters of crude oil and natural gas systems using a radial basis function (RBFNM). The model can predict oil solution Solution Gas-Oil Ratio, oil formation volume factor at bubblepoint, oil viscosity, saturated oil density, evolved gas gravity and undersaturated oil compressibility. He used differential PVT data of ninety samples for training and another ten novel samples for testing the network. Accuracy of the model was compared for training and testing samples to all published correlations. The proposed model is much more accurate than these conventional correlations in predicting the properties of the oils.

In 1999, Al-Shammmasi [23] published a study on neural network model for estimation of bubblepoint pressure and oil FVF at bubblepoint. The bubblepoint model was developed using 137 global data sets for testing trained models, and 1106 for training. The model has two hidden layers, five nodes in the first layer and three in the second layer. The neural model performance shows average absolute error of 15.08%. The oil FVF at bubblepoint model was developed using 180 global data set for testing and 1165 for training. The model has an average absolute error of 11.68%.

In 2001, Osman et al [32] presented an artificial neural network model for predicting the oil formation volume factor at bubblepoint. The model was developed using 803 published data from the Middle East, Malaysia, Colombia, and Gulf of Mexico. One-half of the data was used to train the network, one-quarter to cross-validate the relationships established during the training process and the remaining one-quarter to test the model. The results of their study show that the model gives better prediction and higher accuracy compared to the published empirical correlations, oil formation volume factor at bubblepoint at the bubblepoint with an absolute average percent error of 1.789%, standard deviation of 2.2053% and correlation coefficient of 0.988.

6.5 Artificial Neural Network Architecture Model

Matlab neural network [33] module was used to build the network using backpropagation algorithm with the Levenberg-Marquardt procedure for the optimization procedure.

The artificial neural network solutions have been trained with supervision. In this mode, the actual output of a neural network is compared to the desired output. Weights, which are usually randomly set to begin with, are then adjusted by the network so that the next iteration, or cycle, will produce a closer match between the desired and the actual output. The learning method tries to minimize the current errors of all processing elements. This global error reduction is created over time by continuously modifying the input weights until acceptable network accuracy is reached.

6.5.1 Data Used

In order order to avoid network erratic behaviors during training process, all data used were normalized. This reduced the data to a range from -1 to 1. Each normalized variable is calculated by subtracting the variable value from the mean and divided by standard deviation. Different partitioning ratios were tested (2:1:1, 3:1:1, and 4:1:1). The ratio of 2:1:1 yielded better training and testing results. The data was divided into training, cross validation and testing in the ratio 2:1:1 respectively.

6.5.2 Software Used

Matlab software (version 7) [33] environment was utilized in the modeling. The software offers a good way to monitor the performance of the three set of data (training, validation, and testing) at the same time. A Matlab program was written and training parameters were modified in order to ensure that these parameters are well optimized.

6.6 Network Architecture

A Backpropagation network has been chosen because of its high capabilities to generalize well in problems plagued with significant heterogeneity and nonlinearity. A Backpropagation network is a multi-layer network with more than one hidden layers. It propagates the inputs activity forward while error is propagated backward to adjust the connection weights in order to improve its predictive capabilities. This is continued until a desired minimum error is achieved. There are multiple slabs of neurons in the hidden layer each with a different activation function thus making this kind of network capable of recognizing imperceptible features in the training pattern. The number of data set used for bubblepoint pressure is 1959, solution GOR is 1772, oil FVF at bubblepoint is 2043, oil viscosity at bubblepoint is 1750 and dead oil viscosity is 1809. Various neural network designs with one-hidden, two-hidden and three-hidden layers were considered and tested. The number of neurons in the hidden layer was varied until stable network was achieved. Each successful trained model was tested to ensure that overfitting does not occur and can predict output from inputs that were not seen by the model during training. Table 6-1 shows the models parameters for the 5 PVT parameters studied. The statistical accuracy and the connection weights and biases of the chosen neural network models after several training attempts are shown in Tables 6-2-6-11. The crossplots and histograms of error are shown in Figures 6-4 to 6-13

Table 6-1 Neural Networks Model Parameters

	Input Variables	Input Node	Hidden Layer	Neuron
Pb	γ_o, Rs , T, $\gamma_{g,}$	4	1	5
Rs	γ_g ,Pb, T, γ_o	4	1	4
Bob	γ_o, Rs , T, $\gamma_{g,}$	4	1	6
Viscosity at Pb	γ_g ,Pb, V_d , γ_o	4	1	6
Dead Oil Viscosity, V_d	T, γ_o	2	1	5

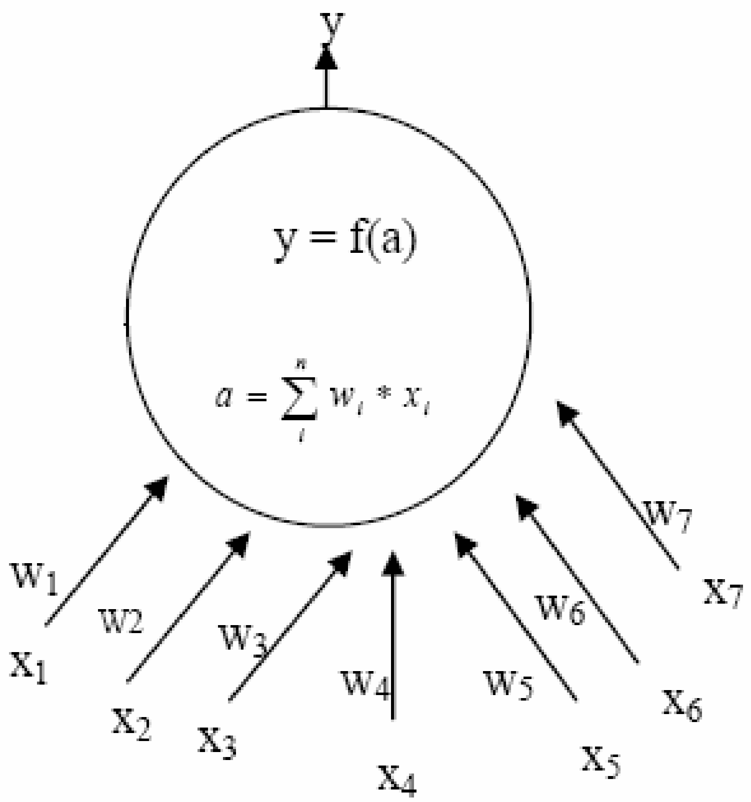

Figure 6-1 Neuron

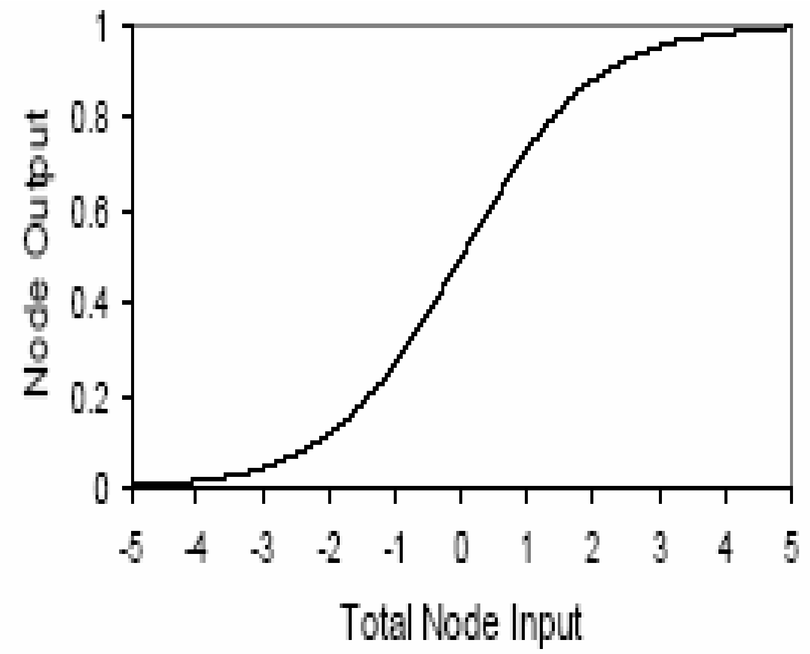

Figure 6-2 Sigmoid Function

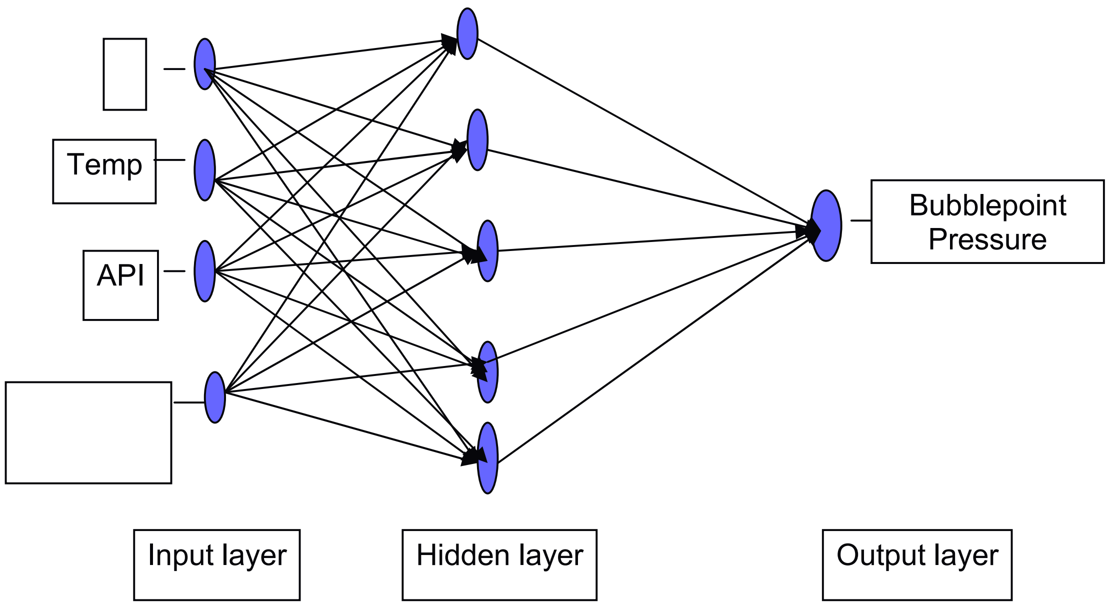

Figure 6-3 Neural Network Model for Bubblepoint Pressure

Table 6-2 Statistical Accuracy of Pb (ANN)

Er	Ea	Emin	Emax	RMS	R	SKEWNESS	KURTOSIS
-0.36217	7.6169	0.017446	34.097	10.365	0.90439	-0.02811	4.3088

Table 6-3 Connection Weights and Biases for Pb

Input Layer					
j/i	wij				bias
	1	2	3	4	bj
1	0.050824	-1.1967	0.32449	-0.21631	0.59547
2	1.2581	0.010609	-0.35464	2.0583	-0.91408
3	0.5209	0.075027	0.66287	-2.2101	0.44777
4	0.17971	5.9186	0.067886	-1.081	6.6093

Hidden Layer					
j/i	wij				bias
	1	2	3	4	bj
1	1.5698	-1.3298	-0.18277	1.8009	-4.2062
2	-0.04547	-2.1959	-0.54017	-2.4591	3.634
3	0.59468	2.6005	-2.3347	-5.2502	3.3137
4	-2.1022	3.2405	-3.3758	0.9799	-2.0114
5	-5.2647	-2.7837	2.7161	6.9769	-2.8097

Output Layer						
j/i	wij					bias
	1	2	3	4	5	bj
	-0.93013	-2.196	6.0489	-3.5293	5.0468	-2.9573

Table 6-4 Statistical Accuracy of GOR (ANN)

Er	Ea	Emin	Emax	RMS	R	VAR	SKEWNESS	KURTOSIS
-2.9237	12.633	0.020366	56.869	16.668	0.93313	296.41	0.206	4.0999

Table 6-5 Connection Weights and Biases for GOR

Input Layer					
j/i	wij				bias
	1	2	3	4	bj
1	1.3428	0.61878	-1.6939	-0.31766	-3.0961
2	-0.88387	-0.30896	0.92033	-0.03625	0.10709
3	-3.0719	3.9665	2.3932	0.019728	-4.2858
4	1.8227	-0.1738	4.6744	-1.9427	0.51219

Hidden Layer					
j/i	wij				bias
	1	2	3	4	bj
1	2.2954	0.73593	-2.149	-2.9222	-1.6088
2	-0.76255	-3.8572	1.5775	-0.31322	0.30447
3	0.34407	0.41114	-1.2354	2.8098	-2.8737
4	0.68055	-2.3393	-1.4613	3.7737	-1.6513
	0.3728	-0.1314	-2.3363	1.9613	0.72068

Output Layer						
j/i	wij					bias
	1	2	3	4	5	bj
	2.669	2.6531	-2.9045	2.341	1.425	-1.9872

Table 6-6 Statistical Accuracy of Oil FVF at Pb (ANN)

Er	Ea	Emin	Emax	RMS	R	VAR	SKEWNESS	KURTOSIS
0.020117	1.6441	0.001094	13.514	2.824	0.98511	7.9901	-0.01072	9.0306

Table 6-7 Connection Weights and Biases for Oil FVF at Pb

Input Layer					
j/i	wij				bias
	1	2	3	4	bj
1	-0.09708	0.40782	0.31711	0.15109	0.28033
2	-0.31688	-0.37138	0.23997	0.056822	1.384
3	-0.29138	-0.06537	0.38511	0.071455	0.20635
4	0.2491	-0.67873	0.17062	0.13407	-0.84926

Hidden Layer					
j/i	wij				bias
	1	2	3	4	bj
1	0.09996	0.042848	0.29241	0.35567	-0.43857
2	0.27075	0.69445	0.003104	0.093952	-0.44224
3	0.57284	-0.93187	-0.56854	0.48355	-0.07537
4	-0.41128	0.16629	0.69879	0.03193	-0.0728
5	-0.15942	0.098442	0.20395	0.39146	-0.19817
6	-0.29095	-0.28498	0.23925	-0.31542	-0.49409

Output Layer							
j/i	wij						bias
	1	2	3	4	5	6	bj
	-0.49216	-0.04144	0.98327	-1.2719	-0.56399	-0.00324	0.28801

Table 6-8 Statistical Accuracy of Oil viscosity at Pb (ANN)

Er	Ea	Emin	Emax	RMS	R	VAR	SKEWNESS	KURTOSIS
-5.1329	14.688	0.002721	103.2	25.369	0.96612	630.53	-4.449	55.388

Table 6-9 Connection Weights and Biases for Oil viscosity at Pb

Input Layer					
j/i	wij				bias
	1	2	3	4	bj
1	0.69088	0.81016	0.40939	0.31859	0.55334
2	-0.0214	-0.00584	0.21736	-0.53651	1.5831
3	-1.0329	2.7269	0.9638	-1.9477	3.3377
4	-0.23139	1.4809	-0.80414	-4.6534	-0.51798

Hidden Layer					
j/i	wij				bias
	1	2	3	4	bj
1	1.541	-0.58182	2.565	-0.0298	-4.4972
2	-0.43686	2.5345	-0.28103	-0.24442	-0.861
3	-0.56153	-3.7573	1.7896	-2.8222	1.6624
4	-0.97246	-2.0771	-1.3551	1.2662	1.8668
5	-2.2485	-0.62954	-2.2665	2.4388	-1.5653
6	-5.6962	1.8472	-7.0645	5.0821	-0.91127

Output Layer							
j/i	wij						bias
	1	2	3	4	5		bj
	-0.43742	-2.0278	3.7205	1.3746	1.4762	6.6952	0.10271

Table 6-10 Statistical Accuracy of Dead-Oil Viscosity (ANN)

Er	Ea	Emin	Emax	RMS	R	VAR	SKEWNESS	KURTOSIS
-16.8	30.82	0.01468	275.5	51.163	0.9114	2353.8	-1.8549	9.7998

Table 6-11 Connection Weights and Biases for the Dead-Oil Viscosity

Input Layer			
j/i	wij		bias
	1	2	bj
1	-0.46656	-1.72	-1.2051
2	0.61663	-7.356	-11.402

Hidden Layer			
j/i	wij		bias
	1	2	bj
1	4.9203	8.6634	-5.6027
2	-1.0288	10.166	-3.176
3	1.7882	3.8506	-3.2564
4	-0.01719	0.91993	-4.0937
5	2.1266	-0.71204	2.8989

	Output Layer					
j/i	wij					bias
	1	2	3	4	5	bj
	3.3834	-5.0186	5.3394	0.095297	0.30508	-0.92081

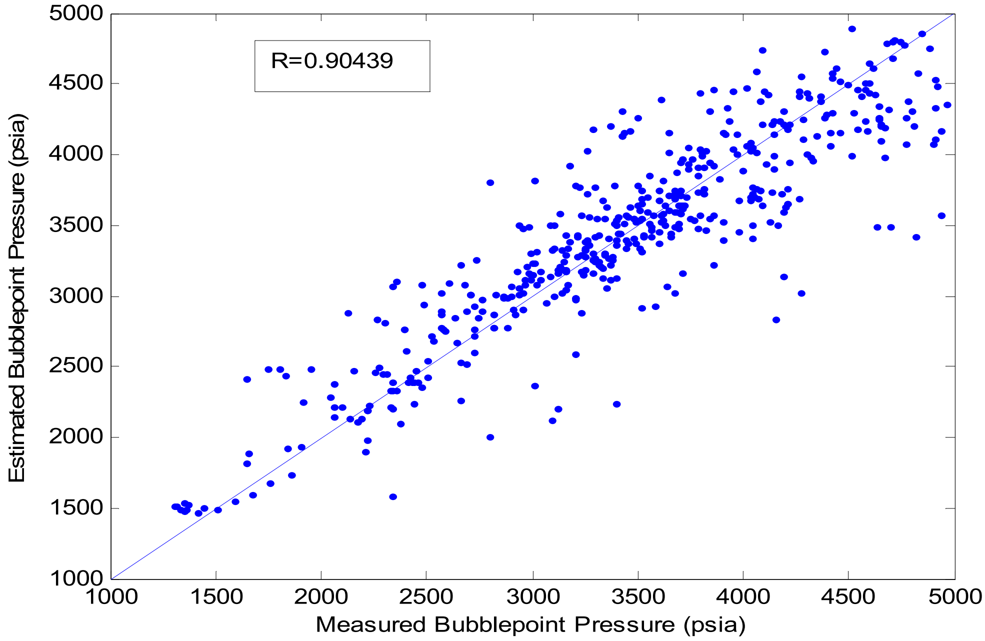

Figure 6-4 Crossplot for Pb (data used for testing)

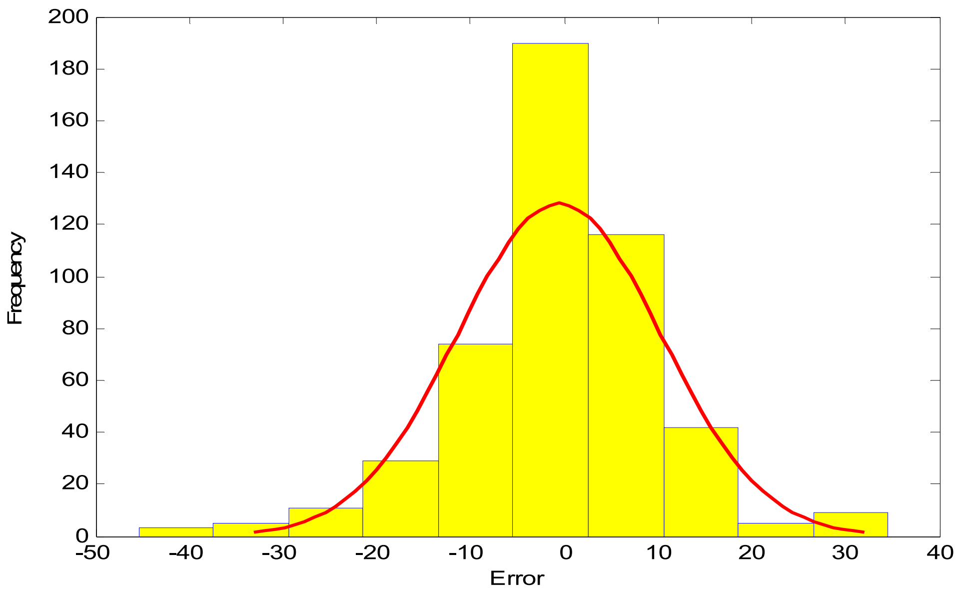

Figure 6-5 Histogram of Errors for Pb (data used for testing)

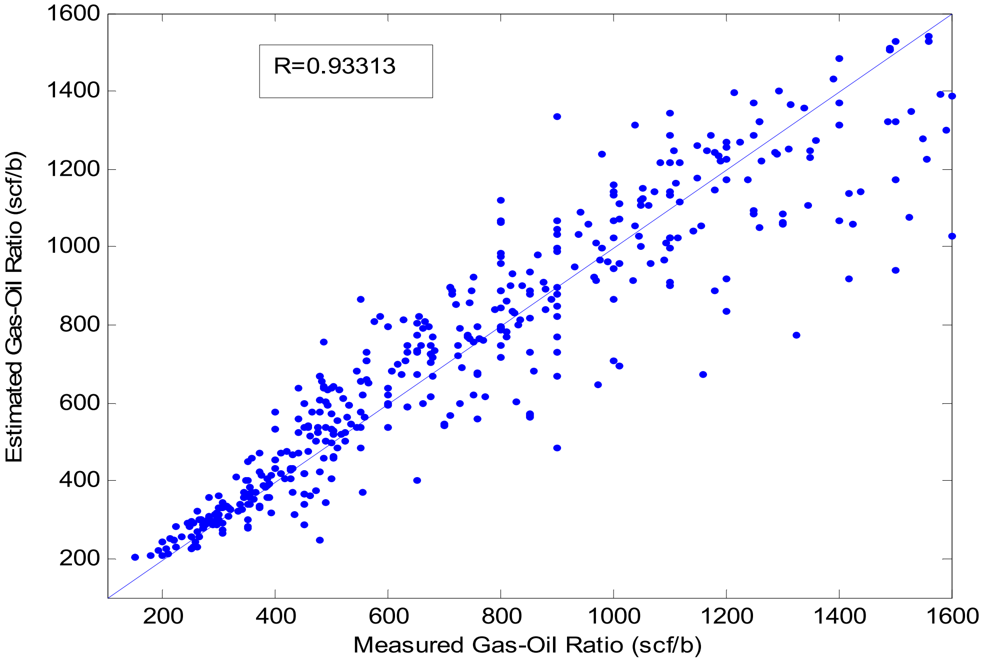

Figure 6-6 Crossplot for Solution GOR (data used for testing)

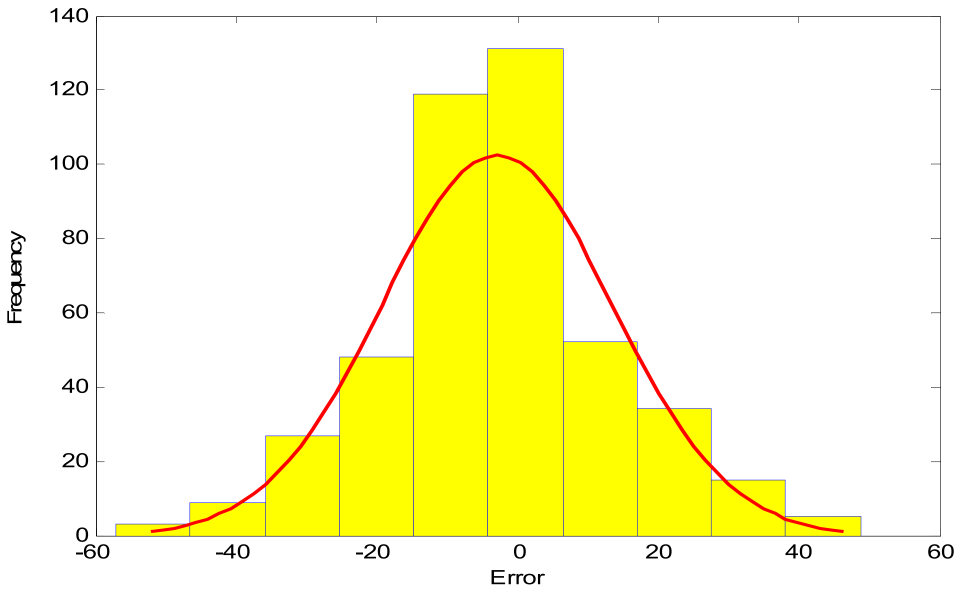

Figure 6-7 Histogram of Errors for Solution GOR (data used for testing)

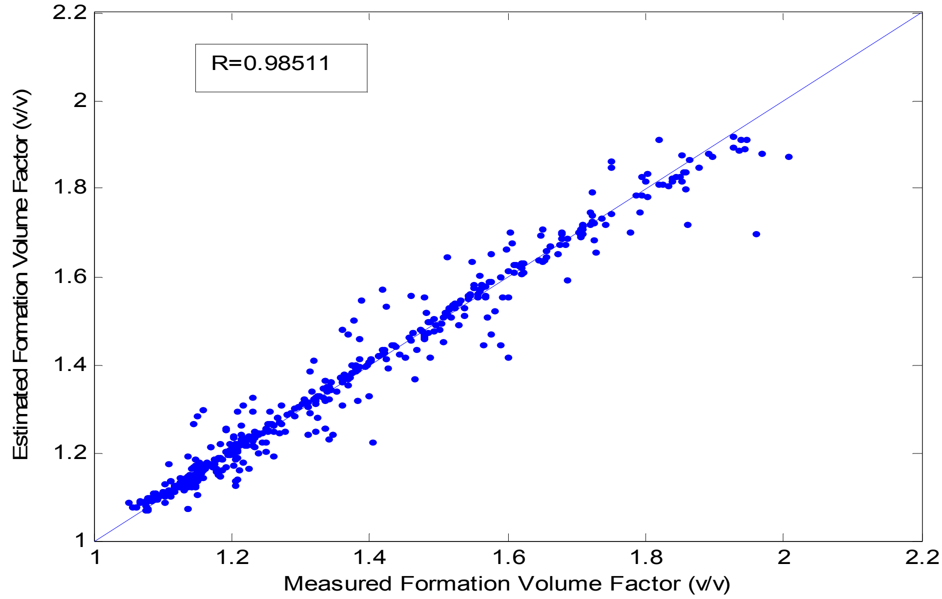

Figure 6-8 Crossplot for Oil FVF at Pb (data used for testing)

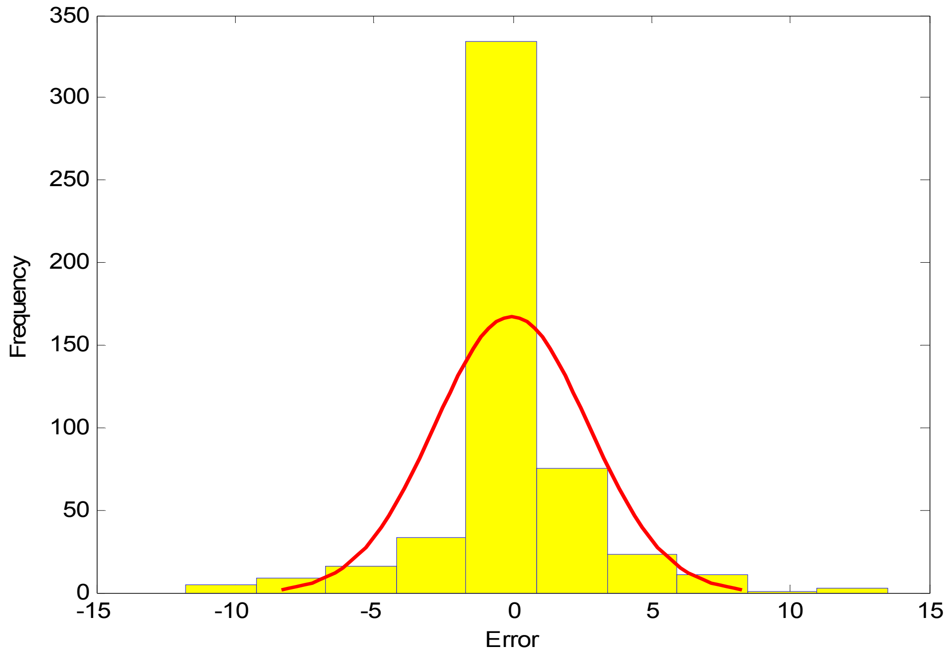

Figure 6-9 Histogram of Errors for Oil FVF at Pb (data used for testing)

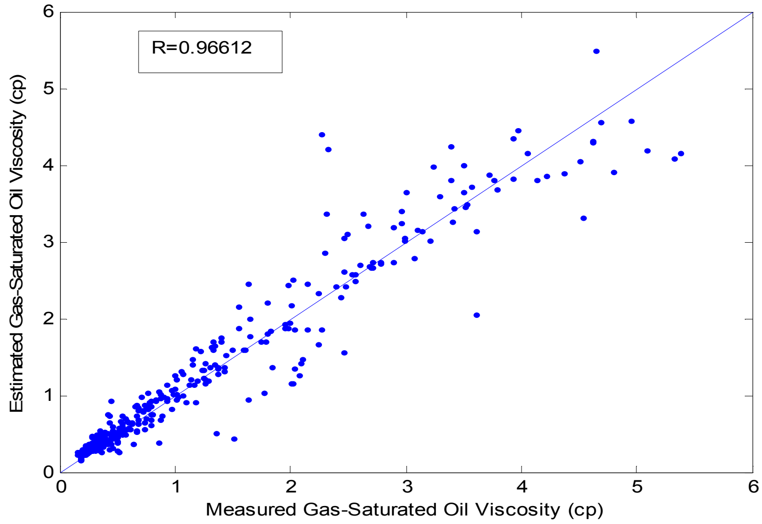

Figure 6-10 Crossplot for Oil viscosity at Pb (data used for testing)

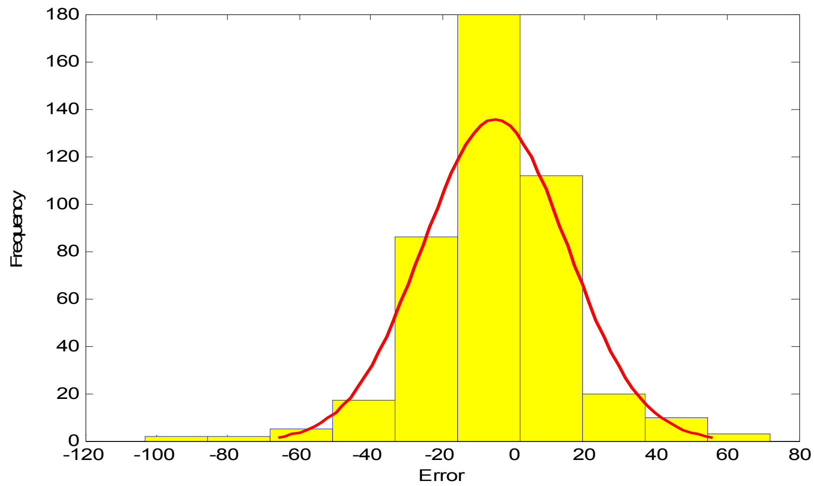

Figure 6-11 Histogram of Errors for Oil viscosity at Pb (data used for testing)

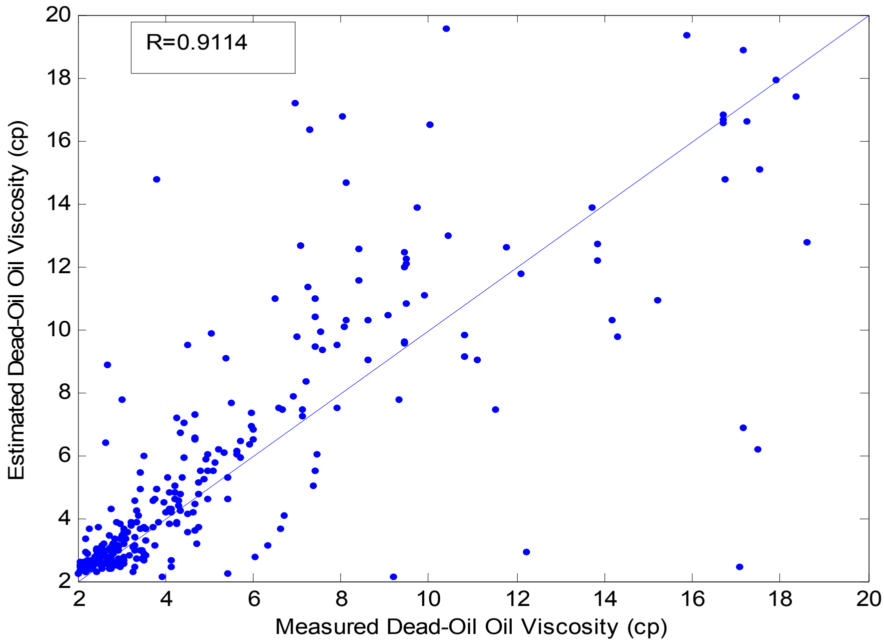

Figure 6-12 Crossplot for Dead-Oil Viscosity (data used for testing)

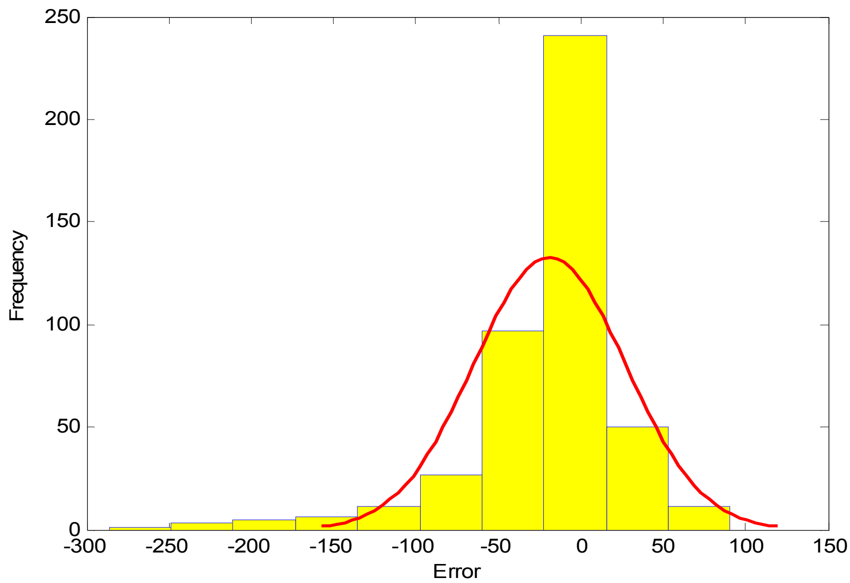

Figure 6-13 Histogram of Errors for Dead-Oil Viscosity (data used for testing)

Chapter 7

Discussions of Results

7.1 Bubblepoint Pressure

Comparison of statistical analysis of the correlations with original and recalculated coefficients based on Nigerian crudes shows a major improvement in errors in Standing, Vasquez and Beggs, Glaso and Al-Marhoun correlations. Table7-1 shows the average absolute relative error for original and recalculated coefficients and ANN model. Based on the original coefficient, Standing is recommended for Nigeria data. However, after tuning, Glaso correlation performs better than Standing correlation, therefore, is the most accurate bubblepoint correlation for use for Nigerian crude. The bubblepoint pressure neural network model shows a substantial improvement over numerical correlations with average absolute relative error of 7.62. Its prediction is much more accurate than the best correlation.

7.2 Solution Gas-Oil Ratio

Evaluation using original coefficients shows that Vasquez and Beggs correlation performs better. Table7-2 shows the average absolute relative error for original and recalculated coefficients and ANN model. Staistical analysis indicates that modified Vasquez and Beggs correlation has the least error and predicts averagely better at higher solution GOR unlike other correlations. Either with old or new coefficient Vasquez and Beggs solution GOR correlation is the best for Nigerian crude. The solution GOR neural network model shows significant improvement over the most accurate numerical correlations with average absolute error of 12.633. Its prediction is much more accurate than the best correlation.

7.3 Oil Formation Volume Factor

The results of evaluation using original coefficients show that Al-Marhoun(1992) is slightly more accurate than Standing correlation. Table7-3 shows the average absolute relative error for original and recalculated coefficients and ANN model. The results show that Al-Marhoun average absolute error is almost the same except that Al-Marhoun (1992) correlation has the least variance and the highest R. Besides, Al-Marhoun error distribution shows highest kurtosis of 16.024. In light of this, either with new or old coefficients, Al Marhoun (1992) correlation is the best for Nigerian crude. The oil FVF at bubblepoint neural network model shows some improvement over numerical correlations with average absolute relative error of 1.6441.

7.4 Oil Viscosity at Bubblepoint Pressure

Evaluation using original coefficient of the correlations studied shows that Beggs and Robinson correlation is the most accurate and is the only one that performs well at higher viscosity. After the recalculation of coefficient, Beggs and Robinson correlation still performs better than other correlation, therefore, is the most accurate oil viscosity at bubblepoint correlation for use for Nigerian crude. Table7-4 shows the average absolute relative error for original and recalculated coefficients and ANN model. The oil viscosity at bubblepoint neural network model shows a substantial improvement over numerical correlations with average absolute relative error of 14.688.

7.5 Dead-Oil Viscosity

The statistical analysis of evaluation results using original coefficients show that Beggs and Robinson correlation is the most accurate. Table7-5 shows the average absolute relative error for original and recalculated coefficients and ANN model. Using new coefficients, Glaso correlation is the most accurate correlation for use for Nigerian crude. The dead oil viscosity neural network model shows a substantial improvement over numerical correlations with average absolute relative error of 30.82.

Table 7-1 Bubblepoint Pressure Results

Correlation	Ea with Original Coefficient	Ea with Recalculated Coefficient	Ea Neural Network
Standing(1947)	14.24	11.85	7.62
Glaso(1980)	16.86	11.19	
Vasquez and Beggs(1980)	14.97	11.96	
Al-Marhoun(1988)	24.85	11.42	

Table 7-2 Solution Gas-Oil Ratio Results

Correlation	Ea with Original Coefficient	Ea with Recalculated Coefficient	Ea Neural Network
Standing(1947)	22.23	16.51	12.63
Glaso(1980)	19.32	16.46	
Vasquez and Beggs(1980)	17.41	16.47	
Al-Marhoun(1988)	28.16	20.07	

Table 7-3 Oil Formation Volume Factor at Bubble Point Results

Correlation	Ea with Original Coefficient	Ea with Recalculated Coefficient	Ea Neural Network
Standing(1947)	3.48	3.10	1.6441
Glaso(1980)	3.73	3.097	
Vasquez and Beggs(1980)	4.40	2.58	
Al-Marhoun(1988)	3.28	2.58	

Table 7-4 Oil Viscosity at Bubble Point Results

Correlation	Ea with Original Coefficient	Ea with Recalculated Coefficient	Ea Neural Network
Chew & Connally	75	22.71	14.69
Beggs & Robinson	31	21.06	
Labedi	116	27.03	
Khan	58	43.45	

Table 7-5 Dead Oil Viscosity Results

Correlation	Ea with Original Coefficient	Ea with Recalculated Coefficient	Ea Neural Network
Beal	46.88	42.84	30.82
Beggs & Robinson	42.08	42.09	
Glaso	44.96	41.15	
Labedi	53.88	46.22	

Chapter 8

Conclusions and Recommendations

8.1 Conclusions

The following conclusions were drawn from this study

1. Standing correlation is the best for prediction of bubblepoint pressure with original coefficients using Nigerian data. However, after tuning, Glaso and Al-Marhoun (1988) correlations are better.
2. Vasquez and Beggs correlation with original and new coefficients predicts better than other correlations.
3. Al-Marhoun (1992) oil FVF correlation with original and new correlation is the best due to its low error, highest correlation coefficient and the least variance.
4. Beggs and Robinson correlation with original and new coefficients is the most accurate for predicting oil viscosity at bubblepoint because of the least error.
5. Beggs and Robinson correlation with original coefficients is the most accurate for predicting dead-oil viscosity. Using new coefficients, Glaso correlation is the most accurate correlation.
6. Higher accuracy was obtained when correlation are tuned to the regional data.
7. This study shows that present practice in Nigeria of using only Standing and Vasquez & Beggs correlations for Pb, Rs and Bob estimation is not the optimum.
8. Neural network models predictions are better for all PVT properties studied.

8.2 Recommendations

The following recommendations are made for future works

1. Study should be conducted on other PVT properties such as compressibility, Bt, and Viscosity below bubblepoint.
2. The results of this study indicate that a substantial better accuracy could be achieved by using the recommended correlations to predict PVT properties in Nigeria oil industry.

APPENDIX A: STATISTICAL PARAMETERS

The following statistical parameters are used to determine and compare the accuracy of the correlations

1. **Average percent relative error**

$$E_r = \frac{1}{n_d}\sum_{1}^{n_d} E_i$$

Where

$$E_i = \left(\frac{X_{meas} - X_{est}}{X_{meas}}\right)_i \times 100(i = 1, 2, ...n_d)$$

E_r shows the relative deviation of calculated values from experimental values. The lower the value of E_r, the more equally distributed are the errors between positive and negative values.

2. **Average absolute percent relative error**

E_a is the relative absolute deviation of calculated values from experimental values. The lower the E_a the better the correlation.

$$E_a = \frac{1}{n_d}\sum_{1}^{n_d} E_i$$

3. **Maximum absolute percent errors**

$$E_{\max} = \max_{1}^{n_d} |E_i|$$

4. **Minimum absolute percent errors**

$$E_{\min} = \min_{1}^{n_d} |E_i|$$

5. **Root mean square Error**

$$RMS = \sqrt{\sum_{i=1}^{n_d} (E_i)^2 / n_d}$$

RMS is the measure of the closeness of correlation prediction to the measured values.

6. **Skewness**

Skewness is a parameter that describes asymmetry in a random variable's probability distribution. Normal distributions will have a skewness value of approximately zero. Right-skewed distributions will have a positive skewness value; left-skewed distributions will have a negative skewness value.

$$skewness = \left(\frac{1}{n_d}\right)\sum_{i=1}^{n_d}\left(\frac{x_i - \overline{x}}{s}\right)^3$$

7. **Kurtosis**

Kurtosis characterizes the relative peakedness or flatness of a distribution compared with the normal distribution. Positive kurtosis indicates a relatively peaked distribution. Negative kurtosis indicates a relatively flat distribution.

$$kurtosis = \left[\left(\frac{1}{n_d}\right)\sum_{i=1}^{n_d}\left(\frac{x_i - \overline{x}}{s}\right)^4\right] - 3$$

8. **Coefficient of correlation**

The correlation coefficient quantifies the degree of linear association between two variables. It is typically denoted by r and will have a value ranging between negative 1 and positive 1.

$$R^2 = 1 - \sum_{1}^{n_d}\left(x_{meas} - x_{est}\right)_i^2 / \sum_{1}^{n_d}\left(x_{meas} - x_{est}\right)_i^2$$

Where $\overline{x}$ is the mean

APPENDIX B: PVT CORRELATIONS

A.1. Bubblepoint pressure

A1.1. Standing (1947)

$$P_b = a_1 (R_s / \gamma_g)^{a_2} e^{a_3 T + a_4 \gamma_{API}} \tag{A-1}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	18	5.3452
a_2	0.83	0.633
a_3	2.09535 x10^{-3}	0.078367
a_4	- 28.78231 x10^{-3}	-0.58399

A1.2. Glaso (1980)

$$P_b = e^{a_1 + a_2 \ln C + a_3 (\ln C)^2}$$
$$C = (R_s / \gamma_g)^{a_4} T^{a_5} \gamma_{API}{}^{a_6} \tag{A-2}$$

Coefficient	Original	*Modified correlation for Nigerian data*
a_1	4.06844	0.27957
a_2	1.7447	1.92
a_3	-0.13124	-0.10998
a_4	0.816	1.0809
a_5	0.172	0.56892
a_6	-0.989	-1.1085

A1.3. Vasquez & Beggs (1980)

$$P_b = a_1 (R_s / \gamma_g)^{a_2} e^{a_3 \gamma_{API} / (T + 460)} \tag{A-3}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
For $\gamma_{\mathrm{API}} \le 30$:		
a_1	20.7880	1.7434
a_2	0.9143	0.71814
a_3	-23.5202	-0.50115
For $\gamma_{\mathrm{API}} > 30$:		
a_1	29.7818	2.3836
a_2	0.8425	0.5262
a_3	-20.1609	-0.70891

A1.4. Al-Marhoun (1988)

$$P_b = a_1 R_s^{a_2} \gamma_g^{a_3} \gamma_o^{a_4} (T + 460)^{a_5} \tag{A-4}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	5.38088 x10^{-3}	2.9055
a_2	0.715082	6.3323 x x10^{-1}
a_3	-1.87784	-5.1727 x10^{-1}
a_4	3.14370	3.2911
a_5	1.32657	0. 21254

A.2. Solution gas oil ratio

A2.1. Standing (1947)

$$R_s = a_1 \gamma_g P_b^{a_2} e^{a_3 T + a_4 \gamma_{API}} \quad \text{(A-5)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	30.7343×10^{-3}	0.024297
a_2	1.2048	1.164019
a_3	-2.5245×10^{-3}	-0.0010122
a_4	34.677×10^{-3}	0.041036

A2.2. Glaso (1980)

$$R_s = \gamma_g (C \times_{API}{}^{a_4} / T^{a_5})^{a_6}$$

$$C = 10^{\left(a_1 - (a_2 - a_3 \log 10(P_b))\right)^{0.5}} \quad \text{(A-6)}$$

Coefficient	Original	*Modified correlation for Nigerian data*
a_1	2.8869	2.876
a_2	14.1812	14.935
a_3	-3.3093	-2.7823
a_4	0.989	0.57979
a_5	0.172	0.07.182
a_6	1.2255	2.0301

A2.3. Vasquez & Beggs (1980)

$$R_s = a_1 \gamma_g P_b^{a_2} e^{a_3 \gamma_{API} / (T + 460)} \quad \text{(A-7)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
For $\gamma_{\mathrm{API}} \leq 30$:		
a_1	0.0362	0.093033379
a_2	1.0937	0.983019587
a_3	25.7240	22.98339
For $\gamma_{\mathrm{API}} > 30$:		
a_1	0.0178	0.023212
a_2	1.1870	1.2608
a_3	23.9310	13.266

A2.4. Al-Marhoun (1988)

$$R_s = a_1 \gamma_g^{a_2} P_b^{a_3} \gamma_o^{a_4} (T + 460)^{a_5} \tag{A-8}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	1.4903 x10^{+3}	1390.7
a_2	1.3984	0.85293
a_3	2.6260	1.377
a_4	-4.3963	-5.8615
a_5	-1.8600	-1.9249

A.3. Oil formation volume factor at bubblepoint pressure

A.3.1. Standing (1947)

$$B_{ob} = a_1 + a_2 [R_s (\gamma_g / \gamma_o)^{a_3} + a_4 T\,]^{a_5} \tag{A-9}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	0.9759	0.8086

a_2	0.00012	0.0000754
a_3	0.5	1.421705
a_4	1.25	4.297418
a_5	1.2	1.25198

A3.2. Glaso (1980)

$$B_{ob} = 1 + 10^{(a_3 + a_4 * C + a_5 * C^2)}$$

$$C = \log 10(R_s(\gamma_g / \gamma_o)^{a_1} + a_2 T \qquad \text{(A-10)}$$

Coefficient	Original	*Modified correlation for Nigerian data*
a_1	0.526	0.42632
a_2	0.968	5.9705
a_3	6.58511	9.1691
a_4	2.91329	3.4045
a_5	-0.27683	-0.21651

A.3.3. Vasquez & Beggs (1980)

$$B_{ob} = 1 + a_1 R_s + a_2 (T - 60)\left(\gamma_{API} / \gamma_g\right) + a_3 R_s (T - 60)\left(\gamma_{API} / \gamma_g\right) \qquad \text{(A-11)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
For $\gamma_{API} \leq 30$:		
a_1	0.4677 x10^{-3}	3.5474 x10^{-4}
a_2	17.51 x10^{-6}	1.2362 x10^{-5}
a_3	-18.11 x10^{-9}	-1.5263 x10^{-13}
For $\gamma_{API} > 30$:		
a_1	0.467 x10^{-3}	1.935 x10^{-4}
a_2	11.00 x10^{-6}	2.36 x10^{-5}
a_3	1.337 x10^{-9}	2.47 x10^{-8}

A.3.4. Al-Marhoun (1992)

$$B_{ob} = 1 + a_1 R_s + a_2 R_s\left(\gamma_g/\gamma_o\right) + a_3 R_s\left(T-60\right)\left(1-\gamma_o\right) + a_4\left(T-60\right) \quad \text{(A-12)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	0.177342 $\times 10^{-3}$	1.273 $\times 10^{-4}$
a_2	0.220163 $\times 10^{-3}$	2.68 $\times 10^{-7}$
a_3	4.292580 $\times 10^{-6}$	1.30 $\times 10^{-5}$
a_4	0.528707 $\times 10^{-3}$	1.036 $\times 10^{-3}$

A.3.5. Petrosky & Farshad (1993)

$$B_{ob} = a_1 + a_2\left[R_s^{a_3}\left(\gamma_g^{a_4}/\gamma_o^{a_5}\right) + a_6 T^{a_7}\right]^{a_8} \quad \text{(A-13)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	1.0113	0.99408
a_2	7.2046 $\times 10^{-5}$	3.4125 $\times 10^{-6}$
a_3	0.3738	0.41954
a_4	0.2914	4.8544$\times 10^{-5}$
a_5	0.6265	1.1212
a_6	0.24626	0.38294
a_7	0.5371	0.75045
a_8	3.0936	3.2114

A-4 Oil Viscosity at Bubblepoint

A.4.1. Chew and Connally (1959)

$$\mu_{ob} = \alpha \mu_{od}^{\ \beta} \quad \text{(A-14)}$$

$$\alpha = a_1 + a_2 e^{a_3 R_s}$$

$$\beta = a_4 + a_5 e^{a_6 R_s}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	0.2	1.998×10^{-1}
a_2	0.8	1.69
a_3	-1.86509×10^{-3}	-5.22×10^{-3}
a_4	0.43	0.30422
a_5	0.57	0.31892
a_6	-1.65786×10^{-3}	-3.30×10^{-7}

A.4.2. Beggs and Robinson (1975)

$$\mu_{ob} = \alpha \mu_{od}^{\beta} \tag{A-15}$$

where

$$\alpha = a_1 (R_S + a_2)^{a_3}$$

$$\beta = a_4 (R_S + a_5)^{a_6}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	10.715	10.722
a_2	100	99.99989
a_3	-0.515	-0.54649
a_4	5.44	5.446154
a_5	150	150
a_6	-0.338	-0.32977

A.4.3. Labedi (1992)

$$\ln \mu_{ob} = a_1 + a_2 \gamma_{API} + a_3 \ln \mu_{od} + a_4 \ln p_b \tag{A-16}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	5.397259	7.2235
a_2	-0.081557	-0.086696

a_3	0.6447	0.44647
a_4	-0.426	-0.68665

A.4.4 Khan et al

$$\mu_{ob} = \frac{a_1\sqrt{\gamma_g}}{\sqrt[3]{R_s}\,\theta_r^{a_2}(1-\gamma_o)^3}$$

$$\theta_r = \frac{T + 459.67}{459.67} \quad \text{(A-17)}$$

Coefficient	Original	*Modified correlation for Nigerian data*
a_1	0.09	0.016981
a_2	4.5	1.582

A.5. Dead oil viscosity

A.5.1Beal (1946)

$$\mu_{od} = [a_3 + (a_4)/api^{a_5}][360/(T+200)]^a$$

where

$$a = 10^{(a_1 + a_2/api)} \quad \text{(A-18)}$$

Coefficient	Original	*Modified correlation for Nigerian data*
a_1	0.43	5.2412 x10^{-8}
a_2	8.33	8.7036
a_3	0.32	0.53293
a_4	1.8 x10^7	1.8 x10^7
a_5	4.53	4.4387

A.5.2. Beggs and Robinson (1975)

$$\ln(\ln(\mu_{od}+1)) = a_1 + a_2\gamma_{API} + a_3\ln T \qquad \text{(A-19)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	7.816432	3.9685
a_2	-0.04658	-0.065697
a_3	-1.163	-0.27922

A.5.3. Glaso (1980)

$$\ln\mu_{od} = a_1 + a_2\ln T + a_3\ln(\ln\gamma_{API}) + a_4(\ln T)\ln(\ln\gamma_{API}) \qquad \text{(A-20)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	54.56805426	47.851
a_2	-7.179530398	-5.7798
a_3	-36.447	-36.609
a_4	4.478878992	4.5039

A.5.4. Labedi (1992)

$$\ln\mu_{od} = a_1 + a_2\ln\gamma_{API} + a_3\ln T \qquad \text{(A-21)}$$

Coefficient	*Original correlation*	*Modified correlation for Nigerian data*
a_1	21.23904	22.261
a_2	-4.7013	-4.8131
a_3	-0.6739	-0.86445

REFERENCES

1. NNPC, Nigerian National Petroleum Corporation. Annual Report, 2002.

2. OPEC, OPEC Statistical Bulletin. 2002.

3. Standing, M.B., *A pressure-Volume-Temperature correlation for mixtures of California oil and gases.* Drilling and Production Practice. Am. Pet. Inst.Tulsa OK, 1947: p. 275-287.

4. Lasater, J.A., *Bubblepoint correlation.* Trans. AIME (Am. Inst. Min. Metall.), 1958. **213**(1958): p. 379-381.

5. Vasquez, M.E. and H.D. Beggs, *Correlation for fluid physical property prediction.* Journal of Petroleum Technology, 1980. **32**(6): p. 968-970.

6. Vasquez, M.E., *Correlations for Fluid Physical Property Prediction*, in *Petroleum Engineering*. 1976, University of Tulsa: Tulsa.

7. Glaso, O., *Generalized pressure-volume-temperature correlations.* Journal of Petroleum Technology, 1980. **32**(5): p. 785-795.

8. Al-Marhoun, M.A., *PVT correlations for Middle East crude oils.* Journal of Petroleum Technology, 1988. **40**(5): p. 650-666.

9. Dokla, M. and M. Osman, *Correlation of PVT Properties for UAE crudes.* SPE Formation Evaluation, 1992: p. 41-46.

10. Petrosky Jr, G.E. and F.F. Farshad, *Pressure-Volume-Temperature correlations for Gulf of Mexico.* SPE paper # 26644, 1993: p. 395-406.

11. Omar, M. and A. Todd, *Development of new modified black oil correlations for Malaysian crudes.* SPE paper # 25338, 1993(1993): p. 211-219.

12. Al-Marhoun, M.A., *New Correlations for formation volume factors of oil and gas mixtures.* Journal of Canadian Petroleum Technology, 1992. **31**(3): p. 22-26.

13. Chew, J. and J. Connally, C. A, *A viscosity correlation for gas-saturated crude oils.* Trans. AIME (Am. Inst. Min. Metall.), 1959(216): p. 23-25.

14. Beggs, H.D. and J.R. Robinson, *Estimating the viscosity of crude oil system.* Journal of Petroleum Technology, 1975(9): p. 1140-1149.

15. Khan, S.A., et al., *Viscosity correlations for Saudi Arabian crude oils.* SPE Paper # 15720, 1987: p. 251-258.

16. Abu-Khamsin, S.A. and M.A. Al-Marhoun, *Development of a new correlation for bubblepoint viscosity.* The Arabian Journal for Science and Engineering, 1991: p. 99-105.

17. Labedi, R., *Improved correlations for predicting the viscosity of light crudes.* Journal of Petroleum Science and Engineering, 1992. **8**(1992): p. 221-234.

18. Beal, C., *The viscosity of air, water, natural gas, crude oil and its associated gases at oil field temperature and pressures.* Trans. AIME (Am. Inst. Min. Metall.), 1946(165): p. 94-112.

19. Ostermanm, R. and O. Owolabi, *Correlations for the reservoir fluid properties of Alaskan.* SPE Paper # 11703, 1983(1983): p. 357-366.

20. Saleh, A.M., I.S. Mahgoub, and Y. Assaad, *Evaluation of empirically derived PVT properties for Egyptian oils.* SPE paper # 15721, 1987.

21. Sutton, R.P. and F.F. Farshad, *Evaluation of Empirically derived PVT properties for Gulf of Mexico crude oils.* SPE Reservoir Engineering, 1990: p. 79-86.

22. Mahmood, M.A. and M.A. Al-Marhoun, *Evaluation of empirically derived PVT properties for Pakistani crude oils.* Journal of Petroleum Science and Engineering, 1966. **16**(1996): p. 275-290.

23. Al-Shammasi, A.A., *Bubblepoint Pressure and Oil Formation Volume Factor Correlations.* SPE Paper # 53185, 1999.

24. Al-Marhoun, M.A., *Evaluation of empirically derived PVT properties for Middle East crude oils.* Journal of Petroleum Science and Engineering, 2004. **42**(2004): p. 209-221.

25. Negnevitsky, M., *Artificial Intelligence*. First ed. 2002, London: Pearson Education Limited. 394.

26. Dowla, F.U. and L.L. Rogers, *Solving problems in environmental engineering and geosciences with artificial neural networks*. First ed. 1995, London: The MIT press. 239.

27. Mahgoub, I.S., *Neural Network: What it can do for Petroleum Engineers.* SPE Paper # 29219, 1995.

28. Mohaghegh, S. and S. Ameri, *Artificial Neural Network as a valuable tool for Petroleum Engineers.* SPE Paper # 29220-Prepared as an unsolicited paper for SPE, 1995.

29. Gharbi, R.B. and A.M. Elsharkawy, *Neural-network model for estimating the PVT properties of Middle East crude oils.* SPE paper # 37695, 1997.

30. Gharbi, R.B. and A.M. Elsharkawy, *Universal neural-network model for estimating the PVT properties of crude oils.* SPE paper # 38099, 1997.

31. Elsharkawy, A.M., *Modeling the properties of crude oil and gas systems using RBF network.* SPE Paper # 49961, 1998: p. 151-166.

32. Osman, M., O.A. Abdel-Wahab, and M.A. Al-Marhoun, *Prediction of oil PVT properties using neural networks.* SPE Paper # 68233, 2001.

33. MATLAB, *Neural network toolbox tutorial*. 2004

VITA

Adeeyo Yisa Ademola is a graduate of Petroleum Engineering from King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia. He obtained bachelor and master of engineering from Federal University of Technology, Akure, Nigeria

Areas of interest are in petroleum fluids phase behavior, PVT modeling and artificial neural networks.